UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

THE IMPACT OF SOCIOECONOMIC AND FIRST-GENERATION STATUS ON STEM-MAJOR ENROLLMENT

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

MASTER OF SCIENCE

By

KATIE HOLLOWAY
Norman, Oklahoma
2020

THE IMPACT OF SOCIOECONOMIC AND FIRST-GENERATION STATUS ON STEM-MAJOR ENROLLMENT

A THESIS APPROVED FOR THE
DEPARTMENT OF PSYCHOLOGY

BY THE COMMITTEE CONSISTING OF

Dr. Lori Snyder, Chair

Dr. Shane Connelly

Dr. Jorge Mendoza

Acknowledgements

First and foremost, I would like to thank my advisor, Dr. Lori Snyder. Your guidance and encouragement has been invaluable throughout this project. Thank you also to my committee members, Dr. Shane Connelly and Dr. Jorge Mendoza, for giving me your time and for your thoughtful recommendations. Thank you especially to my parents and friends. I am so grateful to have your continuous and relentless support. I would not be here without all of you. Thank you.

Table of Contents

Abstract ... vi
Introduction ... 1
Social Cognitive Career Theory ... 4
Social Cognitive Career Theory: Background/Contextual Affordances ... 6
Social Cognitive Career Theory: Person Inputs ... 10
Social Cognitive Career Theory: Learning Experiences ... 11
Social Cognitive Career Theory: Self-Efficacy ... 13
Social Cognitive Career Theory: Proximal Contextual Influences ... 16
Method ... 19
Sample ... 19
Procedure ... 21
Survey Measures ... 22
Analyses ... 25
Results ... 28
Discussion ... 34
Limitations ... 39
Future Directions ... 40
Conclusions ... 42
References ... 44
Table 1 ... 58
Table 2 ... 59
Table 3 ... 60
Table 4 ... 63
Table 5 ... 64
Figure 1 ... 65
Figure 2 ... 66
Figure 3 ... 67

Abstract

In order to maintain leadership and competitiveness in a global economy driven by science, technology, engineering, and mathematics (STEM), the United States needs to increase representativeness of its STEM workforce and leaders. Several studies have indicated that significant issues of underrepresentation remain in STEM despite national investments in training and program grants intended to promote diversity. The present study focuses on two groups that are currently underrepresented in STEM: individuals from low-income backgrounds and individuals of first-generation status. Further, the sample majority consisted of undergraduate students who identify as American Indian/Alaskan Native, who are notably underrepresented in both research and STEM. The present study uses social cognitive career theory (SCCT) as a frame to investigate factors that may explain the role of socioeconomic and first-generation status on undergraduate enrollment in a STEM major. Results indicate mixed findings on the predictive value of social class but reveal new proximal predictors of STEM-major enrollment. New methods for attracting students into STEM, limitations, and future research directions are discussed.

Keywords: Social Cognitive Career Theory, STEM, SES, first-generation status

Introduction

The United States is persistently concerned with maintaining global leadership competitiveness in science, technology, engineering, and mathematics (STEM; National Science Board, 2010). Currently, the United States has extensive opportunity to meet this goal by increasing representativeness within the STEM workforce and its leaders. Past implicit and explicit biases on top of a myriad of other factors have hindered the growth of diversity in STEM. In this context, diversity refers to members of gender or ethnic groups who have historically been underrepresented in STEM. This includes women, African Americans, American Indian Alaska Natives (AIAN), Hispanics, and Pacific Islanders (Office of Science and Technology Policy, 2016). In comparison to the general population, the representation for racially minoritized groups in STEM fields is disproportionately lower than it is for both Whites and Asians. For example, African Americans, Hispanics, and AIAN together account for 27% of the U.S. population, yet in 2016, underrepresented minorities accounted for just 22% of all science and engineering degrees awarded that year. The disparity grows larger when examining the professional gaps, where only 13% of STEM professionals are members of underrepresented minorities. These gaps are even further demonstrated at the doctoral level; for example, although African Americans account for 12% of the population, they only accounted for 4% of all science and engineering doctoral degrees earned in 2015 (National Science Board, 2018).

In addition to gender and ethnicity, diversity in the contexts of higher education and STEM also extends to members of low socioeconomic status (SES) and first-generation status, which refers to students whose parents did not attain a college degree. Individuals from the fastest growing segments of the population, including low-income families, are the least likely to earn a college degree. Students from the lower quartile of socioeconomic status are significantly more likely to leave STEM by dropping out of college in comparison to their peers from higher income backgrounds (Chen, 2013) and these educational attainment gaps are only continuing to grow (Kelly, 2005; Mortenson, 2006; Western Interstate Commission for Higher Education (WICHE), 2003). These results are also demonstrated among first-generation students, who are significantly underrepresented in both higher education and STEM (Engle & Tinto, 2008). It is critical to note that low-income students and first-generation students disproportionately consist of racial minorities, which contributes to the complicated, intersectional experiences these students may face in attaining higher education (Engle & Tinto, 2008).

The lack of diverse individuals in STEM may be a contributing factor to the lack of social mobility opportunities for women and racially minoritized groups, which can also exacerbate economic disparities (Soo Oh & Lewis, 2011). Further, this under-representation of minoritized groups in STEM may contribute to minority health gaps (Satcher & Pamies, 2005). For example, discrimination, bias, and prejudice are all noted as contributors to racial and ethnic disparities in accessible health care (Nelson, 2002). However, when diverse individuals succeed in STEM, this provides an opportunity for financial stability. Undergraduate students who major in STEM are more likely to seek jobs that are related to their major than students enrolled in non-STEM majors. This may provide more opportunities for employment since students are likely be better able to capitalize on the knowledge and skills they gain during their undergraduate career. Further, research has indicated that individuals who attain alignment between their college major and employment are more likely to earn more, maintain longer employment, and have higher levels of life satisfaction (Xu, 2013). Thus, not only do STEM careers provide an opportunity for financial success, these careers may also help individuals perceive their lives more favorably.

With these considerations, the current study focuses on identifying factors that promote or dissuade undergraduate enrollment in STEM majors.

Lastly, the current study explored a notably understudied sample of underrepresented students: American Indian Alaska Native undergraduates. In comparison to Asian, White, and Hispanic students, AIAN students have the lowest rate of graduation from high school (National Science Foundation, 2013). AIAN students are underrepresented in gifted and talented programs, have lower GPA and SAT scores, and are less likely to take advanced placement (AP) exams (Miller, 2004). Additionally, AIAN students are less likely to enroll in college and have a decreased likelihood to graduate with a college degree in comparison to Asians and Whites (National Science Board, 2010). In degree attainment, only 0.6% of students who graduate with a STEM bachelor's degree are AIAN (Fiegener, 2015), despite making up 2% of the population (Jones & Ramirez, 2010). When examining these statistics, it is imperative to recognize that numbers are not neutral and cannot represent the totality of the experiences AIAN students face. Education was and continues to be a powerful tool utilized to force students to assimilate into the mainstream, predominantly White culture. The experiences of AIAN students in education is directly connected to a history of Indian boarding schools that utilized punitive measures and enforcement of the English language and Christian values to "kill the Indian and save the man" (Pratt, 1892, pp. 260-271; Tippeconnic III & Tippeconnic Fox, 2012). AIAN students in education may face cultural conflict, especially in STEM where there may be incompatibilities between Western science and traditional values (Alkholy et al., 2017). This historical and ongoing oppression towards AIAN students continues to affect their educational pathways (Writer, 2001). Although this paper is centered on the cross-racial/ethnic experiences of students from various social status backgrounds, it is critical that researchers understand the experiences of AIAN students. In sum, the purpose of the current study is to provide additional knowledge about the role of SES and first-generation on undergraduate STEM-major enrollment. In addition, this study aimed to further understanding of the experiences of AIAN students, as most previous research has not included a large enough sample to examine this group.

Social Cognitive Career Theory

Social Cognitive Career Theory (SCCT) was used as a conceptual framework to guide the selection of predictors that influence enrollment in a STEM major (Lent et al., 1994). Based on an expansion of Bandura's work, SCCT assumes that person inputs (i.e., gender and race/ethnicity) and background/contextual characteristics (i.e., SES) interact in influencing career-related behaviors (Bandura, 1986). Specifically, SCCT posits that past learning experiences influence an individual's self-efficacy (beliefs in their competency in completing a task) and outcome expectations (beliefs about probable outcomes), which then impact career interests, choice goals, and choice actions (i.e., enrolling in a STEM major). In addition, person inputs and background/contextual characteristics impact various proximal contextual influences, such as barriers and supports, which subsequently affect career-relevant choice actions (Lent et al., 1994, 2000). Figure 1 provides an overall illustration of the SCCT model.

The SCCT framework has been shown to provide a good fit to the data for first-generation and low-income students with respect to predicting math and science interests and goals (Garriott et al., 2013). This model may be especially useful in capturing experiences unique to SES and first-generation students due to its focus on both individual and contextual factors (L. Y. Flores et al., 2017). Additionally, research focusing on intersectionality, which refers to the relationship between joint social identities and psychological outcomes and consequences has been gaining in popularity (Cole, 2009). Understanding the relations among social class variables across all racial/ethnic groups can improve the content of career interventions and counseling (Fouad & Brown, 2000). Despite this, existing SCCT literature offers only minimal research on how exposure to educational and career opportunities may affect the relationship between social class and career choice goals. Further, SCCT research also contains little in regards to the intersectionality of social class using an Asian and AIAN sample (L. Y. Flores et al., 2017). Thus, the proposed study sought to utilize the SCCT framework to examine these understudied populations.

The current study utilized a revised version of the full SCCT model. Specifically, the present study examined the influence of person inputs and background/contextual affordances on learning experiences. Learning experiences were expected to predict self-efficacy. In turn, self-efficacy was proposed to predict career choice actions. Additionally, the proposed study examines the impact of background/contextual affordances on proximal contextual influences, which were predicted to affect career choice actions. Lastly, two additional paths in the SCCT model were added: from background/contextual affordances to choice action and from background/contextual affordances to proximal contextual influences.

For the current study, the person inputs were gender and race. The variables of interest are those that were unique to the current study or that have been identified in research as most likely to contribute to the SCCT model. In the present effort, the primary variable of interest, background/contextual affordances, was operationalized as Family SES, School SES, and first-generation undergraduate status. Learning experiences included ACT math score and the number of advanced placement math and science courses taken in high school. Self-efficacy was measured by math self-efficacy and identity as a scientist. The secondary variable of interest, proximal contextual influences, was defined by financial stress, concern with finding a job locally, and communal orientation. The hypothesized model and variable relationships are provided in Figure 2. The following sections provide further discussion of these proposed relationships.

Social Cognitive Career Theory: Background/Contextual Affordances

In the present study, the focal block of interest in the SCCT framework was background/contextual affordances. These attributes were examined to understand how they may serve as pathways through which group membership influences STEM enrollment. These contexts and learning backgrounds influence the progression from learning experiences, to self-efficacy, to choice actions. This set of main variables are theorized by Lent and colleagues to be environmental influences that begin in early childhood and can continue to affect the individual (Lent et al., 1994). Regarding enrollment in a STEM major, Lent and colleagues proposed that the development of knowledge and interest in STEM, and subsequent enrollment in a STEM major, are influenced by group socialization and norms (1994). As such, the present study examines individuals from diverse backgrounds (i.e., socialized backgrounds) and how those backgrounds may influence their learning experiences, current day proximal influences, and career choice actions.

Socioeconomic Status. In a study conducted by Engle and Tinto (2008), students having an annual household income under $25,000 are classified as low income. Students who come from a low socioeconomic background face unique challenges in their post-secondary schooling experiences, such as having fewer opportunities and more disadvantages in attaining higher education. These students are more likely to be older, receive less financial support from parents, and work full-time. In turn, these multiple obligations affect their ability to be fully involved in college integration opportunities, such as study groups, interactions with faculty, or participation in extracurricular activities (Engle & Tinto, 2008). Additionally, students from low socioeconomic backgrounds have an increased likelihood of leaving the institution after their first year, even after controlling for academic and financial factors (Engle & Tinto, 2008; Fenske et al., 2000; Stinebrickner & Stinebrickner, 2003). In the context of STEM-related variables, low SES individuals have lower mathematic achievement and progress in comparison to their higher SES peers (Graham & Provost, 2012). and are less likely to take AP math and science courses in high school, which could dissuade them from pursuing a STEM career (Wang & Degol, 2013).

Currently, the value of SES as a predictor for choosing a STEM major is equivocal, which may be due to inconsistencies in how socioeconomic status is measured. Therefore, the current study specifies two SES variables to be examined: Family SES and School SES. Family SES can be defined as a combination of all or some of the following variables: parental education, parental occupation, family income, and/or perceived social ladder status. Using only occupational prestige as a socioeconomic predictor, male and female students whose fathers were in a professional or executive position were more likely to choose an engineering or science major (Leppel et al., 2001). However, a study that used just family income as a proxy for SES found that higher SES students were more likely to choose a non-lucrative major such as the humanities (Ma, 2009). Other studies have found that, by itself, Family SES was not related to college major choice (Niu, 2017; X. Wang, 2013). The discrepancies in these research findings may also be due to many studies examining samples of only low-income students (L. Y. Flores et al., 2017). Thus, this study aims to include a variety of students from differing SES backgrounds to reduce range restriction and better clarify the relationship between Family SES and choice of major.

For the purposes of this study, School SES is defined by the number of students that qualify for free or reduced lunch at the participant's high school. A high School SES indicates a high number of students who qualify for free or reduced lunch. A student's School SES negatively correlates with the number of math and science subjects taken (Li et al., 2009), high school achievement and SAT score (Crisp et al., 2009), and math self-efficacy (Cordero et al., 2010), which all positively correlate with STEM enrollment (Rumberger & Palardy, 2005). The learning experiences of students in low SES schools may also be a contributor to disparities in math and science achievement. For example, students in low-income areas are more likely to experience less qualified teachers, more likely to face low expectations, and their schools have less funding per student in comparison to schools in higher-income areas (Alfinio. Flores, 2007). Only a few studies have indicated the predictive value of School SES on STEM-major enrollment. For example, Orr et al. (2011) found that students from high School SES backgrounds were less likely to enroll in engineering majors. Similarly, Niu (2017) found that even when taking into account the qualifications of their math teachers, SAT math score, and highest level of mathematics completed in high school, students from low School SES environments reported higher rates in STEM enrollment. School SES likely impacts the educational resources that a student is offered, which affects their learning experiences and subsequent self-efficacy. School SES also appears to impact STEM-major enrollment directly. Despite this finding, the SCCT literature has yet to include examination of School SES on STEM-major enrollment. Thus, the following hypotheses are proposed:

Hypothesis 1: Family SES will have a direct, positive relationship with enrollment in an undergraduate STEM major.

Hypothesis 2: School SES in high school will have a direct, negative relationship with enrollment in an undergraduate STEM major.

First Generation Students. Parental education is an important predictor of both college enrollment and degree attainment for all students (Astin & Oseguera, 2005; Terenzini et al., 1996). The education level of a parent can increase the human, cultural, and social capital that they can provide to their child. For example, college-educated parents have greater access to resources through social networks and familial relationships that allow them to help their child navigate the financial, informational, and social obligations and opportunities of college. Students from families who have only minimal educational support or knowledge, such as first-generation students, may be at a significant disadvantage in comparison to their non-first-generation peers. A lack of relevant social connections and resources may leave first-generation students making less informed decisions about applying and preparing for college (Bradley & Corwyn, 2002; Coleman, 1988; Dika & Singh, 2002; Hossler et al., 1999; McDonough, 1997). First-generation students represent at least 25% of the undergraduate population; however, only 26% of low-income or first-generation students graduate with a bachelor's degree. Although first-generation students may initially be only slightly underrepresented in STEM enrollment, they are the most likely out of all diversity groups to not complete their degree (Anderson & Kim, 2006). Graduation rates for students who are both low-income and of first-generation status drop further to 11% (Engle & Tinto, 2008), compared to the 55% graduation rate of higher-income non-first-generation students.

The academic preparation for college among first-generation students differs significantly in comparison to that of non-first-generation students. Past studies have indicated that first-generation students are more likely to come from low-income backgrounds, receive less family support related to attaining a college degree, and spend less time with family (Terenzini et al., 1996). They are more likely to work full-time in college, have more loans, and maintain a lower GPA (Martinez et al., 2009). Additionally, first-generation undergraduate students are likely to have less access and understanding of information relevant to college success (Pascarella et al., 2004). Regarding STEM, first-generation students may face additional barriers such as lower quality learning experiences in math and science (Bloom & College, 2007) and lower self-perception of preparedness in mathematics (Dika & D'Amico, 2016). Given these findings, this study seeks to further examine the relationship between first-generation status and STEM-major enrollment.

Hypothesis 3: First-generation status will have a direct, negative relationship with enrollment in an undergraduate STEM major.

Social Cognitive Career Theory: Person Inputs

The SCCT person inputs model encompasses person-related variables such as gender and ethnicity. These personal characteristics may evoke specific reactions determined by the socio/cultural environment, which then influence career-relevant experiences (Lent et al., 1994). In contrast to background/contextual affordances, which examine environmental influences, person-inputs are centered on individual and internal factors. These internal characteristics are proposed as having a great influence on an individual's social identity, which can then affect learning experiences and self-efficacy. A plethora of previous research has supported the distinctive influence of person inputs, like gender and race, as STEM career-relevant variables (Crisp et al., 2009; Fouad & Santana, 2017; Lent et al., 2018, p. 20; Ma, 2009; Niu, 2017; Turner et al., 2017). However, in a study by Turner and colleagues (2017), gender was not found to influence STEM actions. Thus, although the focus of the present study is not on person inputs, these person-centered factors were included to control for their potential influence on STEM-major enrollment.

Social Cognitive Career Theory: Learning Experiences

The next area of the SCCT model examines how past learning experiences influence the development of sources for self-efficacy. Classical definitions of learning experiences include performance accomplishments, vicarious learning, verbal persuasion, and physiological arousal (Lent et al., 1994). Enhancing past learning experiences (e.g. taking AP math and science courses) can improve the likelihood of an individual pursuing a STEM career. Past SCCT research has supported this notion, finding that enhanced learning experiences influenced math/science self-efficacy and subsequent math/science goals (Garriott et al., 2013). Despite this key role, few studies have delved into the influence of socioeconomic-related background variables on learning experiences. Although Garriott and colleagues examined social class, as measured by parental education, household resources, and perceived social status, the unique influences of each indicator on learning experiences was not examined. As such, the present study aims to utilize a variety of socioeconomic background influences, including both school- and family-related variables, and their unique influences on learning experiences, self-efficacy, and pursuit of a STEM career.

Outside of the SCCT framework literature, past research has indicated that pre-college experiences and preparation affect college experiences (Crisp et al., 2009). For example, students who take AP math and science courses in high school are more likely to enroll in a STEM major (Wang & Degol, 2013). Further, this exposure to AP math and science courses was found even more influential on entrance into STEM above and beyond math achievement and math self-efficacy. Thus, the present effort examined past academic achievement and past opportunities for science and math development. Individual preparation in math and science during middle and high school has been identified as a critical factor in developing students' learning experiences, self-efficacy, and later interests in STEM, particularly mathematics (Shoffner & Dockery, 2015; DeThomas, 2017). Scholars have recommended that interventions in middle school and high school target skill development in math and science, as this enables students to pursue more AP coursework (Valla & Williams, 2012), enhancing learning experience and helping to develop self-efficacy (Navarro et al., 2007). In fact, this may be the best way to develop self-efficacy within the SCCT framework, as personal success and exposure to mathematics and sciences was found to be the most powerful source of self-efficacy in a sample of high school students (Lopez & Lent, 1992). DeThomas found a similar trend among sophomore college STEM students, with those who were placed in higher-ability mathematics classes in middle and high school reporting significantly higher levels of mathematics self-efficacy. Specific hypotheses related to past learning experiences are discussed further in the paper.

ACT Math Score and Number of Advanced Placement Math & Science Courses Taken. Highly-educated, high-earning families are better able to prepare their children for college level mathematics and science courses. For example, educated, high-SES parents are more likely to encourage their children to enroll in AP math courses (Useem, 1992). This enhanced preparation in math and science can significantly impact rates of STEM enrollment. High school achievement in the form of test scores has been shown to predict whether a student will enroll in a STEM major (Crisp et al., 2009), and the number of math courses taken in high school has been shown to reflect persistence in STEM (Maltese & Tai, 2011). Research conducted by Niu (2017) suggests that higher-SES students were more likely to enroll in a STEM major if they had a high SAT math score; however, this effect was not maintained for students from low SES backgrounds. In fact, low-SES students were not any more likely to enroll in a STEM major even if they had a high SAT math score, suggesting these students may be deterred from entering STEM due to factors other than just past math achievement, such as financial or familial concerns.

These results may also capture differences in math preparation and exploration. For example, opportunities for math and science learning are stratified by socioeconomic status with higher socioeconomic families providing more opportunities for science exploration through after-school activities and summer camps (Duncan & Murnane, 2011). Thus, the current study explored a variety of school-related mechanisms that may explain the relationship between social background and enrolling in a STEM major. Specifically, learning experiences by exposure to math and science were accounted for to examine whether background/contextual affordances may have an effect beyond just past experiences.

Hypothesis 4: Family SES will have a direct, positive effect on a) ACT math score, b) the number of AP math courses taken, and c) number of AP science courses taken.

Hypothesis 5: School SES will have a direct, negative effect on a) ACT math score, b) the number of AP math courses taken, and c) number of AP science courses taken.

Hypothesis 6: First-generation status will have a direct, negative effect on a) ACT math score, b) the number of AP math courses taken, and c) number of AP science courses taken.

Social Cognitive Career Theory: Self-Efficacy

Self-efficacy, another critical aspect of the SCCT model, can be defined as an individual's belief in their ability to succeed in a specific domain, and is proposed to influence an individual's subsequent interest, goals, and choice actions in that domain (Lent et al., 1994).

Self-efficacy stems from previous learning experiences, which are influenced by the interactions between person inputs and background/contextual affordances. A recent meta-analysis by Sheu and colleagues have supported such relations where past learning experiences, especially in the form of direct experiences, positively predicted self-efficacy (2018). This research has been further supported in the SCCT choice model, with several studies linking the relationship between self-efficacy and action choices (S. D. Brown & Lent, 2004; Moakler & Kim, 2014; Rittmayer & Beier, 2008). The following section discusses the relationships of self-efficacy for STEM-relevant variables.

Math Self-Efficacy and Identity as a Scientist. As alluded to earlier, self-efficacy beliefs are predictive of interests, which then predict college major choice and career choices (Lent et al., 1994). Past studies have shown that math self-efficacy (Lent et al., 1984; Leslie et al., 1998) and exposure and proficiency in math and science (Anderson & Kim, 2006) predict persistence in a STEM major. Students from low-SES or first-generation status backgrounds may be particularly at risk of developing low math self-efficacy, due to lack of well-trained teachers or lack of teachers credentialed in science education (Muijs et al., 2004; Nasir et al., 2011). In fact, math self-efficacy has been found to mediate the link between SES and both anticipated and actual mathematics grades in high school (Wiederkehr et al., 2015). Given that minority and low-income students are more prone to low self-efficacy, which in turn leads to lower performance, math self-efficacy may help account for why these students might avoid STEM courses and occupations (Betz, 1997; Lent et al., 2005).

Math self-efficacy and choice actions may also be driven by identity formation in the sciences. Research indicates that adolescents actively create an identity that will help them understand their role in the world and help them feel successful and connected in their daily lives

(Adams & Marshall, 1996; Erikson, 1968). Previous literature on student persistence and success in academics indicates that students who identify with context relevant identities are more likely to excel in their academic careers (Eccles & Barber, 1999). Further, research conducted on undergraduate and graduate underrepresented racial/ethnic minority students found that those with higher self-efficacy were more likely to identify as a scientist, which then promoted commitment to a science-related career (Chemers et al., 2011). Students from low-income schools or those of first-generation status may have fewer opportunities to develop a science identity due to the aforementioned limited number of science courses taken, lower numbers of qualified teachers in science, and less exposure to STEM careers (Engle & Tinto, 2008; Alfinio. Flores, 2007). Thus, a goal of the present study will be to examine the extent to which identity as a scientist affects enrollment in a STEM major.

Hypothesis 7: ACT math score will have a direct, positive effect on a) math self-efficacy and b) identity as a scientist.

Hypothesis 8: The number of AP math courses taken in high school will have a direct, positive effect on a) math self-efficacy and b) identity as a scientist.

Hypothesis 9: The number of AP science courses taken in high school will have a direct, positive effect on a) math self-efficacy and b) identity as a scientist.

Hypothesis 10: Math self-efficacy will have a direct, positive effect on enrollment in a STEM major.

Hypothesis 11: Identity as scientist will have a direct, positive effect on enrollment in a STEM major.

Social Cognitive Career Theory: Proximal Contextual Influences

The last portion of the SCCT model in the present study examines proximal contextual influences. Proximal contextual influences, as proposed by Lent and colleagues (2000), are variables that are much closer in time to the choice action, as opposed to distal predictors such as person inputs and background/contextual affordances. According to SCCT and past research, proximal contextual influences in the form of social, academic, or financial barriers and supports may significantly impact career-relevant choices (Lent et al., 2001, 2003; Turner et al., 2017; X. Wang, 2013). However, there is scant SCCT literature that has examined how proximal contextual predictors relating to social class influence STEM-major enrollment. Thus, the current study examined financial stress, concern with finding a job locally, and communal orientation. These proximal variables may also help explain why a student's background would impact their choice to enroll in STEM.

Financial Stress & Hours Worked per Week. It is important to note that science, technology, engineering, and mathematics students take longer to graduate than other majors, which can exacerbate the financial concern about enrolling in STEM (Barton, 2003; Fenske et al., 2000). These financial factors have been shown to influence how first-generation and lower-income students select their college and major. For example, in a study by Saenz, Hurtado, Barrera, Wolf, and Yeung (2007), first-generation students indicated that financial assistance or low tuition was of primary concern in their college decision-making process. In another study, underrepresented minorities (URM) in STEM were more concerned about financing college than their non-URM classmates (Hurtado et al., 2010). The stress of financing education then leads to inhibited experiences in academic and social adjustment (Hurtado et al., 2010). Combined with the fact that low-income and first-generation students are more likely to be working full-time and off-campus, this group of students may be more prone to experiencing financial stress. Despite this implication, little to no studies have examined the relationship of financial stress on STEM-major enrollment. Lastly, although a study by Wang (2013) found no direct effect on STEM-major enrollment from hours worked per week, this may have been due to the presence of both positive and negative effects associated with working in college. Hence, the current study aims to examine how the proximal influence of financial stress impacts STEM-major enrollment, and further clarify the relationship between hours worked per week and STEM.

Concern with Finding a Job Locally and Communal Orientation. The structure of many STEM careers assumes the willingness and capability to relocate in pursuit of advanced graduate school or training (Oishi et al., 2007). This is unique in comparison to other fields such as business, where an individual has more opportunities to work within the community in which they have built personal relations. For example, in a qualitative study by Sanez et al. (2007), nearly 27% of first-generation students selected their undergraduate program in part because of its proximity to their home, compared to only 17% of non-first-generation students. In other words, first-generation students indicated that a desire to stay near their local community was a significant factor in selecting their university. Thus, those with less means or flexibility may thus be discouraged from enrolling in a STEM major due to a lack of degree programs close in proximity or a lack of perceived employment opportunities in their home cities. However, this relationship has not been examined. Further, there is little to no research that has examined the relationships between concerns with findings a job locally and STEM-major enrollment.

Communal values, which are held as important to both first-generation students and underrepresented minority students, may also impact the relationship between low-SES and first-generation students and majoring in STEM (Harackiewicz et al., 2016). In comparison to higher-

SES individuals, individuals from low-SES backgrounds are more likely to hold other-oriented values, which may also be captured in communal values (Kraus & Stephens, 2012). With regard to our study sample, AIAN students tend to have high scores on communal measures, which may further promote a desire to stay near their hometown (Smith et al., 2014). Additionally, previous studies have indicated that science coursework may not align with the values of underrepresented minorities (Hurtado et al., 2010). This lack of science interest may be due to perceptions that STEM careers are less communal and collaborative in comparison to other careers such as business or education (Diekman et al., 2017). Further, STEM careers often do not place clear emphasis on giving back to the community (Smith et al., 2014). Thus, the numbers of first-generation and low-income students enrolling in STEM may be impacted by scores on communal and collaboration values. In sum, the present study aimed to illuminate the linkages between background, proximal contextual influences, and enrollment in a STEM major.

Hypothesis 12: Financial stress will have a direct, negative effect on enrollment in a STEM major.

Hypothesis 13: The number of hours worked per week will have a direct, negative effect on enrollment in a STEM major.

Hypothesis 14: Concern with finding a job locally will have a direct, negative effect on enrollment in a STEM major.

Hypothesis 15: Communal orientation will have a direct, negative effect on enrollment in a STEM major.

Hypothesis 16: Family SES will have a direct, negative relationship on a) financial stress, b) the number of hours worked per week, c) concern with finding a job locally, and d) communal orientation.

Hypothesis 17: School SES will have a direct, positive relationship on a) financial stress, b) the number of hours worked per week, c) concern with finding a job locally, and d) communal orientation.

Hypothesis 18: First-generation status will have a direct, positive relationship on a) financial stress, b) the number of hours worked per week, c) concern with finding a job locally, and d) communal orientation.

Hypothesis 19: The relationship between Family SES and enrollment in a STEM major will be mediated by a) financial stress, b) the number of hours worked per week, c) concern with finding a job locally, d) communal orientation.

Hypothesis 20: The relationship between School SES and enrollment in a STEM major will be mediated by a) financial stress, b) the number of hours worked per week, c) concern with finding a job locally, d) communal orientation.

Hypothesis 21: The relationship between first-generation status and enrollment in a STEM major will be mediated by a) financial stress, b) the number of hours worked per week, c) concern with finding a job locally, d) communal orientation.

Method

Sample

Undergraduate students at a south-central research university were invited to participate in an online study examining student experiences. Demographic information was collected from self-reported data obtained from an online, longitudinal student achievement study. The analyses utilized data that consisted of multiple cohorts starting in Fall 2015 and ending in February of the Spring 2020 semester. Apart from semesters Spring 2017, Fall 2017, and Spring 2018, new participants were recruited every semester. Based on the purpose of a larger study examining

AIAN experiences in STEM, only AIAN, Asian, and White students were recruited. These three groups were recruited primarily due to their representative size at the university and to examine the experiences of a diverse group of students. Ethnicity was determined by a combination of both a race check-all-that-apply item, as well as an item which asked how the student ethnically identifies. Due to centuries of inter-racial interactions, the racial background of AIAN individuals is complicated. As such, ethnic identity has been noted as a crucial indicator of who is classified as AIAN (Huyser et al., 2010). Given this, a looser categorization method was used for AIAN participants than for White participants. Participants were categorized as AIAN if they ethnically identified as AIAN and if they selected an AIAN racial background along with one or more other races, and/or if indicated that they were enrolled in a tribe. A similar method was utilized for categorization of Asian participants to be more inclusive of Asian-identifying participants who are mixed-race. For participants that were categorized as Asian, these participants ethnically identified as Asian either alone or along with one or more other races and did not select their race as AIAN. White participants were categorized based upon reporting their race and identifying only as White.

The sample included 541 first year undergraduate students. The majority of participants identified as female (n = 344, 63.6%) in comparison to those who identified as male (n = 197, 36.4%). In terms of race/ethnicity, 43.6% were categorized as AIAN (n = 236), 36.6% as White (n = 195), and 19.8% as Asian (n = 107). Participants ranged in age from 17 to 40 (M = 19, SD = 1.32). Regarding their major, 41.4% of participants were in a non-STEM major (n = 224) and 58.6% of participants were in a STEM major (n = 317). For participants in STEM, 41% were male (n = 131) and 59% were female (n = 186). Additionally, the race/ethnicity makeup of participants in STEM was 42% AIAN (n = 134), 23% Asian (n = 73), and 35% White (n = 110).

The sample included a normal distribution of participants from varying family SES backgrounds, with approximately 25.4% (*n* = 137) of students falling within the first quartile, 41% in the second quartile (*n* = 222), and 33.6% (*n* = 182) in the third quartile of socioeconomic status. Regarding school SES, approximately 27% (*n* = 146) of students came from a high school where the majority of students were on free or reduced lunch. In terms of parental education, 61.7% (*n* = 334) of participants did not identify as a first-generation status student, whereas the remaining 38.3% (*n* = 207) did identify as a first-generation status student.

Procedure

Participants were recruited via email and invited to take a survey that took approximately 30 to 45 minutes to complete. A total of 1,635 survey responses were collected. To meet the current study requirements, participants must have answered at least 60% of the questions on the survey and correctly answer 50% or more of the embedded attention-check questions. This reduced the sample size to 1,174. In addition, participants were excluded from the dataset if they did not answer questions related to their parental income, parental education, and high school. As previously noted, this resultant total sample size was 541 participants. Participant data was utilized if they answered questions pertaining to their parental incomes, parental education, and provided their high school name and location. Participants were compensated with a $20 gift card. The participants were included in the current data analysis if they were of "First Year" academic standing. Classification was determined by credit hours, with "First Year" having accumulated between 1-29 semester hours. With permission from both the university and participant, academic records were accessed to obtain academic standing, major, and ACT math score.

Survey Measures

Demographic Variables. Demographic variables were obtained, including self-reported age, gender, and ethnicity. Gender was coded 0 for males and 1 for females. Ethnicity was coded 1 for AIAN, 2 for Asian, and 3 for White.

Family SES. Family SES was measured by assessing Family Income. Participants reported their combined parental figures' yearly income with values ranging from 1 (Less than $20,000) to 10 (Greater than $200,000).

School SES. School SES was measured by analyzing the percentages of the student body receiving free/reduced-price lunch at each participant's high school. Higher School SES indicated higher percentages of students at the participant's high school who qualified for free/reduced price lunch. Data on school SES was obtained from the National Center for Education Statistics (NCES).

First-Generation Status. In order to assess first-generation status, participants reported their maternal and paternal parental figures' highest level of education attainment with values ranging from 1 (Less than High School diploma or GED) to 9 (Doctoral or Professional degree). The information was recoded such that participants indicating that both parental figures did not obtain a college degree represented first-generation students. This operationalization was based on work by Toutkoushian, Stollberg, and Slaton (2018), which found that college deficits were most prevalent among students whose parents held no bachelor's degrees, in comparison to one college-educated parent.

Financial Stress. Financial stress was adapted from the financial subscale on the College Stress Inventory (Solberg et al., 1993). Using a scale from 1 (Never) to 5 (Very Often), students were asked to rate 8-items. A sample item is "In the last year, how often did you experience difficulty paying student fees next semester." The items were averaged, with higher scores indicating higher levels of financial stress. For this current study, Cronbach's α was .91.

Hours Worked per Week. Participants were first asked if they were currently employed. Students who indicated yes were then asked how many hours they work per week. Answer choices ranged from 1 to 40+ hours a week. Students who indicated no were coded as 0.

Concern with Finding a Job Locally. Concern with Finding a Job Locally was assessed using a 4-item scale that measured the importance of several factors in choosing where the participant wished to live after college (Johnson, Elder, & Stern, 2005). The measure rated items on a Likert-scale ranging from 1 (Not at all Important) to 5 (Extremely Important). The scale was adapted because undergraduate students may not currently live in the same area in which they grew up. Thus, a few items were changed to better reflect this. For example, item 3 originally said "to be in the community where you live now" and item 4 said "to leave this area." The adapted number 3 now states "to live in the community where you were raised" and item 4 states "to leave the area where you grew up" (reverse coded). The items were averaged, with higher scores indicating a desire to find a job in the area in which participants grew up. For this current study, Cronbach's α was .81.

Communal Orientation. Communal orientation was assessed by using a 23-item scale assessing goal endorsement (Diekman et al., 2010). Within the 22-item scale were two subscales, agentic and communal goal endorsement. The measure rated items on a Likert-scale ranging from 1 (Not at all Important) to 7 (Extremely Important). Items were slightly adapted for clarity. For example, instead of "serving community," the item was adapted to state "serving the community." Higher scores on the communal goals were indicative of serving, caring, and helping others. For this current study, Cronbach's α was .86.

Number of Advanced Placement Math Courses taken. Participants were asked to indicate which advanced placement math courses they took during high school. The number of courses taken was summed, with higher scores indicating greater exposure to math in high school.

Number of Advanced Placement Science Courses taken. Participants were asked to indicate which advanced placement science courses they took during high school. The number of courses taken was summed, with higher scores indicating greater exposure to science in high school.

Math Self-Efficacy. Math Self-Efficacy was measured using a reduced 18-item scale adapted from Usher and Pajares (2009). The original scale included 24 items. Six of the items (e.g., “Seeing adults do well in math pushes me to do better”) were excluded because they were not appropriate for the current sample of college-aged students. The items were rated using a scale from 1 (Strongly Disagree) to 6 (Strongly Agree). Sample items are “I have always been successful with math,” “Doing math work takes all of my energy,” and “I image myself working through challenging math problems successfully.” The items were averaged, with higher scores indicating higher levels of math self-efficacy. For this current study, Cronbach’s α was .97.

Identity as a Scientist. Identity as a Scientist was assessed using a modified five-item version of Chemers et al. (2011) Identity as a Scientist measure. Participants were asked to indicate the extent to which they identify as a scientist, using a scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). A sample item is “In general, being a scientist is an important part of my self-image.” The items were averaged, with higher scores indicating higher levels of identity as a scientist. For this current study, Cronbach’s α was .96.

Institutional Records

Major. The majors of participants who gave researchers permission to access their institutional records were collected from the university system. To qualify as enrolled in a STEM major, participants must have been in one of the following fields: engineering, biological sciences, mathematics, physical sciences, or a related field. Related fields include those related to research, innovation, or developing new technology using engineering, mathematics, computer science, or a natural science. When there was ambiguity of the categorization of a major, existing taxonomies and evaluative judgments of the math and science courses required in the major were used as determinants of STEM classification.

ACT Math Score. Participant ACT math score was obtained from their academic records.

Analyses

Prior to executing analyses, the data was examined for assumptions of normality and missing data. Data was analyzed using Mplus Verison 8 (L. Muthén & Muthén, 2018). Variables were considered non-normal if their values of absolute skew were < 3.0 and absolute kurtosis at < 10 (Weston & Gore Jr, 2006). Examination of the data indicated small percentages of missing data and non-normality. The percentages of missing data were all under 0.01%, with the exception of ACT math score at 15.5%. The absence of some ACT math scores is likely attributed to participants who did not take the ACT math test, and thus do not have an ACT math score. In order to further examine the patterns of missingness, the “BaylorEdPsych” package was utilized in R (Beaujean, 2012; R Core Team, 2013). While it is likely not feasible to determine whether missing data is missing completely at random (MCAR), MCAR tests can provide some indirect evidence that the missing data is missing at random (MAR). Little’s MCAR test was not significant, $\chi 2 = 397.72$, $p > .001$, suggesting that the pattern of missingness was not problematic

(Little, 1988). Means, standard deviations, minimum and maximum values, and the percentage of missing data for each measure are presented in Table 1.

Given the binary outcome of enrollment in a STEM major and non-normality of the data, two options were considered: 1) the weighted least square with adjustment in mean and variance (WLSMV) estimator and 2) robust maximum likelihood (MLR). While the WLSMV indicator utilizes probit regression, MLR utilizes logistic regression. Although both approaches are capable of modeling categorial data, WLSMV has been noted as the best option due to its lack of assumption of normally distributed variables (T. A. Brown, 2015). In handling missing data, WLSMV utilizes pairwise present, which holds assumptions of MCAR, where cases of missingness on exogenous covariates are dropped. Due to no missing data on the exogenous covariates, no cases were dropped due to missingness. Further, and perhaps most importantly, WLSMV provides fit indices information, whereas MLR does not. As one of the goals of the present study was to examine whether the SCCT model will provide a good fit to the data, the WLSMV estimator was chosen. Further, the WLSMV can be utilized to conduct chi-squared difference tests for nested models, whereas MLR cannot. In order to compute the chi-square difference tests, the DIFFTEST option in Mplus was utilized (L. Muthén & Muthén, 2018).

Due to the high number of predictor variables and their close theoretical relationship, multicollinearity was checked. Multicollinearity occurs when highly correlated predictor variables inflate the regression coefficients in regression results. This can cause the R-squared and contribution of each predictor variable to be limited in size. In order to examine multicollinearity, the VIF values were examined. VIF values above 10 are cause for concern and indicate a high likelihood of multicollinearity (Hair et al., 2010). The majority of the VIF values were quite close to 1, and no VIF values were > 1.5. Thus, it is unlikely that multicollinearity was occurring. Further, while there were several significant correlation coefficients between the predictor variables, no correlations exceeded .80. Thus, it appears that multicollinearity was not present and model analyses continued. The inter-variable correlations are displayed in Table 2.

Model Analyses

Path analysis, a type of structural equation modeling (SEM), was utilized to model the relationships among all study variables (see Figure 2). This type of SEM analysis was chosen because path analysis can examine the relations among predictors that are also assumed to relate to the dependent variable (Kline, 2015). Further, path analysis provides information on model-data fit. Multiple goodness-of-fit indicators were examined, including: $\chi 2$, Comparative Fit Index (CFI), Tucker-Lewis index (TLI), root-mean-square error of approximation (RMSEA), and the weighted root mean square residual (WRMR). For CFI and TLI, values above $\geq .90$ indicates a good fit, whereas above $\geq .95$ indicates a very good fit of the model to the data (Bentler & Bonett, 1980). RMSEA values above $\leq .05$ indicate very good fit and a value $\leq .10$ indicate good fit (Kline, 2015; Steiger, 1990, 1990). WRMR value at or below .95 indicates good fit (Yu, 2002).

Past SCCT research has most often considered gender and ethnicity as person inputs that predict other endogenous variables in the model. However, a few studies have indicated the value of using these variables as control measures on all endogenous variables, due to their influence on each path of the SCCT model (Navarro et al., 2007; Turner et al., 2017). For example, in a study by Turner (2017) it was found that modeling gender solely as a person input led to significantly worse model-data fit. As such, in order to control for the extraneous confounding effects of person inputs, gender and ethnicity were controlled for across all endogenous variables. An alternative model was also tested where gender and ethnicity were modeled as a person input.

Results

Hypothesized Model Evaluation

Initial examination of the hypothesized model indicated poor model fit to the data when using the WLSMV estimator, $\chi 2(39, N = 541) = 225.57$, $p < .01$; RMSEA = .09 (.08, .1); CFI = .70; TLI = .27; WRMR = 1.45. Although the RMSEA value was within an acceptable range, the $\chi 2$, CFI, TLI, and WRMR indicated a poor-fitted model. Upon examination of the model modification indices, three adjustments to the model were considered. The modification indices suggested allowing for correlations between the residual variances of three observed variables. Due to the theoretical relationship between these variables and their placement within the same set of variables of the SCCT model, paths between the residual correlations were added. First, the residuals between the number of AP math courses and AP science courses taken were freely correlated. Second, the residuals between concern with finding a job locally and communal orientation were freely correlated. Third and last, the residuals between financial stress and the number of hours worked per week were freely correlated.

Hypothesized Final Model

After these modifications, overall results indicated the modified model exhibited overall acceptable fit $\chi 2(36, N = 541) = 88.13$, $p < 0.01$; RMSEA = .05 (.04, .06); CFI = .92; TLI = .78; WRMR = .88. Although the fit index TLI suggest poor fit, the RMSEA, CFI, and WRMR indicators suggest the model does fit the data well. No further modification indices with a substantial value were suggested. In consideration of model parsimony, several paths were removed from analyses (Kline, 2011). Based upon recommendations by Wuensch (2016), paths were trimmed if they did not meet the minimum criteria of $|\beta| < .05$. The finalized, trimmed model (see Figure 3) indicated excellent model fit, $\chi2(47, N = 541) = 97.22$, $p < .01$; RMSEA = .04 (.02, .04); CFI = .95; TLI = .92; WRMR = 0.86. The finalized model accounted for 53.8% of the variance in declaring a STEM major, 26.2% of the variance in math self-efficacy, 17.2% of the variance in financial stress, 12.7% of the variance in ACT math score, 12.1% of the variance in identity as a scientist, 4.1% of the variance in number of AP science courses taken, 6.7% of the variance in number of AP math courses taken, 5.1% of the variance in number of hours worked per week, 3.3% in communal orientation, and 2.1% in concern with finding a job locally.

Alternative Model Evaluation

An alternative model was tested in which gender and ethnicity were not controlled for on each of the dependent variables. Similar to the hypothesized model, initial examination of the alternative model indicated very poor model fit to the data when using the WLSMV method, $\chi2(53, N = 541) = 259.59$, $p < .01$; RMSEA = .09 (.08, 1.0); CFI = .67; TLI = .41; WRMR = 1.54. Examination of the modification indices indicated that the model fit would see significant improvement by allowing a few residuals to correlate. The correlated residuals in the alternative model were the same as those in the hypothesized model: a) number of AP math courses and AP science courses, b) concern with finding a job locally and communal orientation, and c) financial stress and the number of hours worked per week. After the alternative model was modified there were still a few suggested modification indices that had values > 10; however, these modification indices did not align with the SCCT framework.

Alternative Final Model

The alternative model indicated overall poor fit to the data, $\chi2(52, N = 541) = 128.00$, $p < .01$; RMSEA = 0.05 (.04, .06); CFI = .89; TLI = .77; WRMR = 1.01. Although RMSEA was within acceptable range, all other fit indices indicate poor fit. In comparison to the hypothesized model, there is a degradation in goodness of fit for the alternative model $\Delta\ \chi 2$ (14, N = 541) = 33.69, $p < .05$. Thus, this suggests that utilizing gender and ethnicity as a control variable, as opposed to a person input, across all endogenous variables is supported. The goodness-of-fit indicators for the hypothesized and alternative model are presented in Table 5.

Primary Analyses

As depicted in Figure 2, the significant standardized path coefficients ranged from -0.37 to 0.50 ($p < .05$). Parameter estimates for the model, including direct and indirect effects, are in Table 3. In addition, the changes in predicted probabilities are also reported for all variables that significantly predicted enrollment into a STEM major. For calculating entrance into STEM, probit regression analyses were run. The probit coefficient is the change in z score that is related to a one-unit change in X. As this is not easily interpretable, the predicted probability was calculated using the following formula (L. K. Muthén & Muthén, 2009):

$$P(y = 1|X) = F(a + b * X) = F(-t + b1 * \chi_1 + \mathrm{b2} * \chi_2 + \ldots),$$

where F = the standard normal distribution function, a = regression intercept, b = unstandardized probit regression coefficients, t = the threshold of enrollment in a STEM major, and $-t$ = the negative of the probit regression intercept. In the first equation, the probability of $P(y = 1|\, x)$ when all independent variables are held at their mean was calculated. In the second equation, the impact of a one unit change on each independent variable was calculated, where $\bar{x} + 1$, and then the $P(y = 1|\, x)$ was recalculated. The first probability was then subtracted from the second probability, which indicates the effect on the predicted probability of enrollment in a STEM major (where enrollment in a STEM major = 1) when all other independent variables are set to their mean.

Hypothesis 1 – Hypothesis 3

Hypotheses 1 through 3 examined the direct effects from background/contextual affordances to STEM-major enrollment, which controlling for gender and ethnicity. Hypothesis 1, which states that Family SES will have a direct, positive relationship with enrollment in an undergraduate STEM major, was not supported. Instead, the opposite was found, where a one-unit increase in the mean of Family SES predicted a -.03 significant decrease in the probability of enrolling in a STEM major. In other words, an increase in Family SES decreases the likelihood of a student enrolling in a STEM major. Hypotheses 2 and 3 were not supported, indicating no direct effect of School SES and first-generation status on enrollment in STEM ($p >$ .05). Gender and ethnicity were also not predictive of enrollment in a STEM major ($p > .05$).

Hypothesis 4 – Hypothesis 6

Hypotheses 4 through 6 proposed direct effects from background to learning experiences in high school. The background characteristics of Family SES, School SES, first-generation status did not predict ACT math score ($p > .05$). However, the covariates of gender ($\beta = -.19$, $p <$ .001) and ethnicity ($\beta = .13$, $p < .001$) did predict ACT math score. Specifically, females on average had lower ACT math scores in comparison to males. A one-way between-subjects ANOVA was conducted to further explore the relationship between ethnicity and ACT math score. As expected, the one-way ANOVA indicated significant mean differences on ACT math score among AIAN, Native, and White students F(2,454 = 10.05, $p < .000$) Post hoc comparisons using the Tukey HSD test indicated that the mean score on ACT math for AIAN students (M = 24.17, SD = 4.20) was significantly lower than Asian (M = 25.92, SD = 3.91) and White (M = 26.01, SD = 4.75) students ($p < .05$). There were no significant differences between Asian and White students ($p > .05$). The number of AP math courses taken was significantly predicted by Family SES ($\beta = .10$, $p < .05$), but School SES, first-generation status, gender, and ethnicity were not significant predictors ($p > .05$). Interestingly, no variables significantly predicted the number of AP science courses taken ($p > .05$), indicating there may be variables outside of the scope of this study that warrant further examination. Thus, Hypothesis 4 was partially supported, but Hypotheses 5 and 6 were not supported.

Hypothesis 7 – Hypothesis 9

The next set of hypotheses proposed that the learning experiences of ACT math score, number of AP math courses taken, and number of AP science courses taken would predict identity as a scientist and math self-efficacy. Hypothesis 7 was supported ($\beta = .21$, $p < .000$), where ACT math score significantly predicted both identity as a scientist and math self-efficacy ($\beta = .49$, $p < .000$). Thus, higher ACT scores predicted higher identity as a scientist and math self-efficacy. The number of AP math courses taken in high school did not have a direct effect on either identity as a scientist and math self-efficacy ($p > .05$), thus Hypothesis 8 was not supported. There was partial support for Hypothesis 9, where more AP science courses taken in high school significantly predicted higher identity as scientist ($\beta = .32$, $p < .000$), but not math self-efficacy ($p > .05$). Lastly, gender and ethnicity were not predictive of identity as a scientist and math self-efficacy ($p > .05$).

Hypothesis 10 – Hypothesis 15

Hypotheses 10 and 11 state that the self-efficacy variables of identity as a scientist and math self-efficacy will have a direct effect on enrollment in a STEM major. Hypotheses 12 through 15 propose that the proximal contextual influences of financial stress, the number of hours worked per week, concern with finding a job locally, and communal orientation will predict enrollment in a STEM undergraduate major. Identity as a scientist had the largest impact on enrollment in a STEM major. Specifically, a 1-point increase in the mean of identity as a scientist resulted in a .20 increase in their probability of enrollment in a STEM major. Math self-efficacy had the second largest impact on enrollment, where an increase in math self-efficacy of 1-point above the mean increased the probability of STEM-major enrollment by .07. Thus, Hypothesis 10 and 11 were supported. In support of Hypothesis 12, a 1-point increase in the mean of financial stress indicated a .05 decrease in the probability of enrollment in STEM. In other words, higher levels of financial stress negatively predict enrollment in STEM. Contrary to what was expected, Hypothesis 14 was not supported, where a 1-point increase in concern with finding a job locally indicated a .05 increase in the probability of STEM enrollment. Namely, higher concerns with finding a job locally was related to slightly increased predicted enrollment in STEM. Lastly, Hypotheses 13 and 15 were not supported, where the number of hours worked per week and communal orientation did not have an impact on enrollment in a STEM major ($p > .05$). In sum, our results suggest that student concerns with finding a job locally may positively impact the likelihood of their enrollment in STEM. Gender and ethnicity did not increase the probability of enrollment in a STEM major ($p > .05$).

Hypothesis 16 – Hypothesis 21

The last portion of hypotheses proposed a new path between background contextual affordances and proximal influences. Further, mediation analyses were hypothesized, where proximal influences would explain part of the relationship between background variables and enrollment in a STEM major. As predicted in Hypothesis 16, financial stress was negatively predicted by Family SES ($\beta = -.15$, $p < .000$), where higher income predicted lower financial stress. Financial stress was not predicted by School SES and first-generation status ($p > .05$). Similarly, the number of hours worked per week was negatively predicted by Family SES (β = -

.12, $p < .01$), but not School SES and first-generation status ($p > .05$). Concern with finding a job locally was also only predicted by Family SES ($\beta = .04$, $p < .05$). Thus, it appears that as Family SES increases, there is a small increase in scores of concern with finding a job locally. Taken together, Family SES negatively influenced financial stress and the number of hours worked per week, but positively influenced concerns with finding a job locally. There were no significant predictors of communal orientation ($p > .05$). In sum, there was partial support of Hypothesis 16, but no support of Hypothesis 17 and 18.

Lastly, hypothesized indirect effects (i.e., Hypotheses 19-21) were estimated utilizing Mplus's MODEL INDIRECT command and bootstrapping procedures. The following indirect effects were tested: background characteristics (e.g., Family SES, School SES, and first-generation status) on enrollment in a STEM major through proximal influences (e.g., financial stress, number hours worked per week, concern with finding a job locally, and communal orientation). All indirect effects are reported in Table 4. There was only one significant indirect effect. The bootstrapped unstandardized indirect effect from Family SES, financial stress, to enrollment in a STEM major was .05, with a 95% confidence interval that ranged from .01 to .09. As such, the relationship between Family SES and enrollment in a STEM major appears to be partially mediated by financial stress.

Discussion

The present study is one of the first to use SCCT to examine predictors of STEM-major enrollment for a sample of AIAN college students. Further, few studies have examined the influence of proximal characteristics, besides supports and barriers, on enrollment in STEM. The overarching purpose of the study was to examine the influence of variables related to socioeconomic status on STEM-major enrollment and provide clarity in the equivocal literature.

The results indicate that after modifying the hypothesized model, the proposed model provided an acceptable fit to the data. Further, after model trimming, there was excellent model-data fit. Overall, the proposed model explained 53.8% of the amount of variance in undergraduate enrollment in a STEM major.

Despite the overall support of the paths proposed by SCCT, the support for the hypotheses was mixed and sometimes contrary to what was expected. Most notably, first-generation status was not found to be predictive of learning experiences, proximal influences, or enrollment in a STEM major. Despite past research that has found that first-generation status students are underrepresented in undergraduate STEM majors (Chen, 2005), this study found no differences in rate of enrollment based upon first-generation status. This aligns with findings from Crisp and colleagues (2009), who found that in a sample of Hispanic, Asian, and White students, first-generation status was not predictive of enrollment in a STEM major. It may be that despite potential lack of parental knowledge on STEM careers and higher education, first-generation status students are as equally motivated to enter STEM as their non-first-generation status counterparts. Lastly, Family SES was found to negatively influence the probability of STEM-major enrollment. These results reflect the same findings from Ma (2009), in which lower family income increased the likelihood of an individual’s enrollment in a STEM major. There is some indication to suggest that these students may recognize the advantage of future job prospects in STEM, and feel driven to enter STEM in order to gain access to social mobility opportunities (Conrad et al., 2009).

Thus, the current study supports that even distal predictors in the SCCT model may impact choice actions (i.e., STEM-major enrollment). It should be noted that the increase in probability from distal predictors was half that of concern with finding a job locally, math self-efficacy, and financial stress, and about a fifth of the influence on probability of identity as a scientist. The strength of the self-efficacy variables on STEM-major enrollment is unsurprising, considering students who feel more efficacious in a subject are more likely to pursue it through goals and choice actions. Despite this, the significance of Family SES even among variables that are more proximal to choice actions, supports the SCCT proposition that environmental influences continue to affect career choices into adulthood (Lent et al., 1994). In contrast to findings from Niu and Orr et al. (2017; 2011), School SES was not predictive of enrollment in a STEM major. In other words, students from high schools that reported all ranges of students qualifying for free or reduced lunch equally enter into STEM. This finding helps clarify that while STEM enrollment rates among students from high schools that vary in SES may be similar among initial first year enrollment at a university, it may be after students begin their college education when the representation issues occur. For example, as students engage in introductory mathematics and science "gateway" courses in college, they may be discouraged if they were not prepared by their high school education and subsequently leave their STEM major.

Surprisingly, this study's background contextual influences did not predict scores on the ACT math exam. Instead, there was a significant influence of gender and ethnicity on ACT math scores. Specifically, both females and AIAN students were more likely to score lower on their ACT math exam than their male and White or Asian counterparts. These findings align with trends in national datasets, where AIAN students typically score several points lower on the ACT than Asian and White students, with females scoring lower than males (ACT, Inc., 2015; Buddin, 2014). This finding suggests that the influence of an individual's personal identity is more salient in influencing their ACT math score, independent of their social capital resources. It is possible that perceptions of women and minoritized groups not excelling at math may influence how these students expect to do on the ACT test, which can subsequently influence how well they score. Although not predictive of ACT math score and the number of AP science courses taken, Family SES did predict the number of AP math courses taken. Students from higher Family SES backgrounds were more likely to take a greater number of AP math courses. This finding aligns with research by Useem (1992), in which higher-SES parents were more likely to encourage their children to enroll in AP math courses. It may be that parents who have higher incomes have more capacity to provide emotional and instrumental support to their children and encourage them in their educational pursuits. The present study did not illuminate what may predict the number of AP science courses a student takes. There may be indicators beyond the scope of the present study, such as the number of AP science courses offered at the high school, which defines opportunities to take AP science courses. Overall, there appears to be support that some environmental and self-identity characteristics may influence exposure and achievement in the math and sciences.

There also appeared to be some support that these learning experiences impact self-efficacy. Scores on the ACT math test significantly predicted both self-efficacy measures, identity as a scientist and math self-efficacy. Thus, high achievers on the ACT math test are more likely to believe in their math and science success. The number of AP math courses taken did not impact self-efficacy beliefs, and the number of AP science courses only predicted identity as a scientist. Thus, this indicates that mere exposure to math and science courses may not raise self-efficacy as much as achievement. This finding closely aligns with classical definitions of learning experiences, which include performance accomplishments but not exposure (Lent et al., 1994).

Past research has typically examined proximal influences in the forms of supports and barriers. The present study sought to find other proximal influences that may impact enrollment in a STEM major. The findings suggest that, along with the impacts of self-efficacy and Family SES, financial stress and concerns with finding a job locally may play important roles as well. As expected, higher financial stress was found to negatively impact the probability of enrollment in STEM. Additionally, the present findings suggest that financial stress partially explains the negative relationship between Family SES and enrollment in a STEM major. For example, a 2009 national survey of First Year students found that 57.2% of students expressed "some" concerns with their ability to finance their education, and 19.8% indicated "major" concern. In turn, these financial concerns may impact student decision-making about college (Rios-Aguilar & Stolzenberg, 2015; Ruiz et al., 2010). It is likely that this concern combined with perceptions that STEM degrees take longer to complete than non-STEM may dissuade students from deciding to enroll in STEM (Barton, 2003; Fenske et al., 2000). Lastly, contrary to what was expected, higher concerns with finding a job locally positively impacted the probability of enrollment in STEM. Historically, there has been significant growth of STEM employment opportunities in the U.S. (U.S. Bureau of Labor Statistics, 2014). Thus, undergraduate students may perceive that STEM-related jobs are more readily available in their local community in comparison to non-STEM jobs. However, it should be noted that this relationship was small and potentially trivial.

Implications

For education practitioners, the present study suggests that additional pathways aside from high school experiences may impact a student's decision to enroll in STEM. Financially stressed students were less likely to enroll in a STEM major, which highlights the criticality of adequately resourcing students. Students who receive this support may feel better equipped to pursue their STEM career aspirations. In addition to expanding financial aid packages, universities can find other ways in which to financially assist their students. For example, universities could alleviate levels of financial stress by expanding their usage of work-study programs. Alternatively, universities could promote financial literacy courses, which are especially valuable for students from first-generation status or AIAN backgrounds (Carter et al., 2013; Tierney et al., 2007). Outreach workshops designed to educate students about the financial aid process may also positively impact student access to STEM.

Furthermore, education practitioners should consider the impact of student concerns with finding a job locally. Informing students about STEM jobs within their community may increase rates of enrollment in STEM majors. For example, universities could partner with local STEM organizations and create outreach programs that promote local STEM job opportunities. For students who moved away from their community to attend university, these local outreach programs may not be as helpful. Thus, universities could encourage academic advisors to provide supplementary resources for these students informing them about job opportunities in their local communities.

Limitations

Despite the strengths of the current study in revealing additional relationships that may impact STEM-major enrollment, there are several limitations to note. A primary purpose of the study was to examine a severely under-represented sample of students, AIAN undergraduates. Thus, the sample only included AIAN, Asian, and White students at a single south-central university. Therefore, due to this limited sample, findings may not be generalizable to other ethnic/racial groups. Additionally, the inclusion of students in their second semester of college introduced the possibility of participants who may have already left their STEM major or had recently transferred in. Despite this, past research has indicated that after initial STEM enrollment, students do not significantly leave their major until after the third semester (Orr et. al, 2011). Thus, it is likely that the sample still captured the experience of a newly admitted undergraduate student who had yet to transfer major. Due to sample size limitations and model complexity, the study did not run multiple-groups analyses. Therefore, it is possible that the model would not fit across diverse ethnic/racial groups and there could be group-based differences in the strength and significance of path coefficients. In addition, path analysis was chosen to examine the unique relations among predictors and dependent variables. However, path analysis assumes the variables are measured without error. Thus, there may have been issues in measurement that were not accounted for in the analyses. Lastly, there are significant variations in how STEM majors are defined. Given that university institutions and the government may define STEM majors and fields differently, implications may vary depending on how STEM majors are coded.

Future Directions

The number of AP science courses taken was the strongest predictor of identity as a scientist, which was the most influential predictor of STEM-major enrollment. However, the variables in the present study did not predict the number of AP science courses that a student took in high school. As discussed in the limitations, the number of AP science courses taken is bound by the availability of AP science courses at a student's high school. Thus, future research should consider the number of AP science courses taken as a percentage of the number of AP science courses available. In turn, researchers could then examine how someone's background or person attributes would predict the percentage of AP science courses taken, and AP math courses could be examined similarly. If researchers better understood this relationship, this would provide opportunities for interventions, which would in turn increase STEM-major enrollment. It would also be valuable for researchers to consider other influences of self-efficacy, such as vicarious learning or psychological arousal that may more directly shape how efficacious an individual is in their math and science performance.

This study revealed that higher concerns with finding a job locally positively predicted enrollment in STEM. The present effort assumes that this relationship may be due to participant perceptions that STEM jobs are more easily attainable in their local community in comparison to non-STEM jobs. Future research should conduct qualitative studies to further understand this relationship, such as directly asking participants about their perceptions of STEM job availability in their town.

The present effort examined several direct effects of social class variables on initial STEM enrollment rates. However, more research in the SCCT literature is needed to examine how to best support diverse students throughout the course of their undergraduate careers. Longitudinal analyses should be conducted to more accurately examine the impact of Family SES, School SES, and first-generation status on STEM-major enrollment. Additionally, the current study was only able to explain half of the variance in STEM-major enrollment, indicating that there may be nuanced dynamics of how social class may function in influencing STEM choice actions. For example, the present effort did not see any significant relationships between first-generation status students and STEM-related outcomes. Alternatively, there may be other social cognitive variables not examined in the present study that are more influential on STEM-major enrollment. Thus, future research should utilize qualitative methods to examine the impact of social class variables, particularly first-generation status, on STEM enrollment. Future quantitative research should also examine other social cognitive variables that may influence STEM enrollment.

Future research should collect a large enough sample to assess if the final model is invariant across groups. Specifically, multiple group analyses should be conducted to examine model fit across diverse groups and investigate differences in the path coefficients. Lastly, future research that collects a large enough sample size should also consider intersectionality. This study may not have fully captured the experiences of students who hold multiple marginalized identities (i.e., first-generation status, low SES, and ethnically under-represented in STEM). Thus, future research should consider the impact of having multiple social identities on students' experiences in STEM.

Conclusions

Given the need to maintain national competitiveness in STEM, the study sought to identify ways in which the STEM pipeline could be improved to recruit students from historically underrepresented diverse groups. Specifically, the present study helps clarify the relationship of social class indicators on undergraduate enrollment in STEM. The study additionally responds to the need for increased representation of AIAN students. The findings indicate that the SCCT model can be used to better understand the impact of Family SES, School SES and first-generation status on enrollment in STEM. In contrast to past studies, School SES was not predictive of enrollment in STEM or of learning experiences. In alignment with some research, Family SES was negatively related to enrollment in STEM. Notably, first-generation status was not predictive of any relationships. Consistent with past research, self-efficacy in the form of identity as a scientist was the strongest predictor of STEM major-enrollment. The present effort also revealed that proximal influences of financial stress or concerns with finding a job locally significantly impact the probability of entrance into STEM. Further, financial stress was found to partially mediate the relationship between Family SES and enrollment in STEM. This research equips practitioners with new methods to better attract students into STEM majors. In conclusion, the present study provides avenues to consider for future research in pursuit of fully understanding the lives of diverse students in STEM.

References

ACT, Inc. (2015). The Condition of College& Career Readiness 2015 American Indian Students. ACT, Inc.

Adams, G. R., & Marshall, S. K. (1996). A developmental social psychology of identity: Understanding the person-in-context. Journal of Adolescence, 19(5), 429–442.

Alkholy, S. O., Gendron, F., McKenna, B., Dahms, T., & Ferreira, M. P. (2017). Convergence of Indigenous Science and Western Science Impacts Students' Interest in STEM and Identity as a Scientist. Ubiquitous Learning: An International Journal, 10(1), 1–13. https://doi.org/10.18848/1835-9795/CGP/v10i01/1-13

Anderson, E., & Kim, D. (2006). Increasing the success of minority students in science and technology.

Astin, A. W., & Oseguera, L. (2005). Pre-college and institutional influences on degree attainment. College Student Retention: Formula for Student Success, 245–276.

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Englewood Cliffs, NJ, 1986.

Barton, P. E. (2003). Hispanics in science and engineering: A matter of assistance and persistence (p. 44). Educational Testing Service.

Beaujean, A. A. (2012). BaylorEdPsych: R Package for Baylor University Educational Psychology Quantitative Courses. https://CRAN.R-project.org/package=BaylorEdPsych

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88(3), 588.

Betz, N. (1997). What stops women and minorities from choosing and completing majors in science and engineering? Sage Publications, Inc.

Bloom, J., & College, E. L. (2007). (Mis)reading Social Class in the Journey Towards College: Youth Development In Urban America. 26.

Bradley, R. H., & Corwyn, R. F. (2002). Socioeconomic status and child development. Annual Review of Psychology, 53(1), 371–399.

Brown, S. D., & Lent, R. W. (2004). Career development and counseling: Putting theory and research to work. John Wiley & Sons.

Brown, T. A. (2015). Confirmatory factor analysis for applied research. Guilford publications.

Buddin, R. (2014). Gender Gaps in High School GPA and Act Scores. ACT Research & Policy.

Carter, D. F., Locks, A. M., & Winkle-Wagner, R. (2013). From When and Where I Enter: Theoretical and Empirical Considerations of Minority Students' Transition to College. In M. B. Paulsen (Ed.), Higher Education: Handbook of Theory and Research (Vol. 28, pp. 93–149). Springer Netherlands. https://doi.org/10.1007/978-94-007-5836-0_3

Chemers, M. M., Zurbriggen, E. L., Syed, M., Goza, B. K., & Bearman, S. (2011). The Role of Efficacy and Identity in Science Career Commitment Among Underrepresented Minority Students: Efficacy and Identity in Science Career Commitment. Journal of Social Issues, 67(3), 469–491. https://doi.org/10.1111/j.1540-4560.2011.01710.x

Chen, X. (2005). First-generation students in postsecondary education: A look at their college transcripts.

Chen, X. (2013). STEM Attrition: College Students' Paths Into and Out of STEM Fields (p. 104). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Cole, E. R. (2009). Intersectionality and research in psychology. American Psychologist, 64(3), 170–180. https://doi.org/10.1037/a0014564

Coleman, J. S. (1988). Social capital in the creation of human capital. American Journal of Sociology, 94, S95–S120.

Conrad, S., Canetto, S. S., MacPhee, D., & Farro, S. (2009). What attracts high-achieving socioeconomically disadvantaged students to the physical sciences and engineering? College Student Journal, 43(4), 1359.

Cordero, E. D., Porter, S. H., Israel, T., & Brown, M. T. (2010). Math and Science Pursuits: A Self-Efficacy Intervention Comparison Study. Journal of Career Assessment, 18(4), 362–375. https://doi.org/10.1177/1069072710374572

Crisp, G., Nora, A., & Taggart, A. (2009). Student Characteristics, Pre-College, College, and Environmental Factors as Predictors of Majoring in and Earning a STEM Degree: An Analysis of Students Attending a Hispanic Serving Institution. American Educational Research Journal, 46(4), 924–942. https://doi.org/10.3102/0002831209349460

Diekman, A. B., Brown, E. R., Johnston, A. M., & Clark, E. K. (2010). Seeking Congruity Between Goals and Roles: A New Look at Why Women Opt Out of Science, Technology, Engineering, and Mathematics Careers. Psychological Science, 21(8), 1051–1057. https://doi.org/10.1177/0956797610377342

Diekman, A. B., Steinberg, M., Brown, E. R., Belanger, A. L., & Clark, E. K. (2017). A Goal Congruity Model of Role Entry, Engagement, and Exit: Understanding Communal Goal Processes in STEM Gender Gaps. Personality and Social Psychology Review, 21(2), 142–175. https://doi.org/10.1177/1088868316642141

Dika, S. L., & D’Amico, M. M. (2016). Early experiences and integration in the persistence of first-generation college students in STEM and non-STEM majors: FIRST-

GENERATION STEM MAJORS. Journal of Research in Science Teaching, 53(3), 368–383. https://doi.org/10.1002/tea.21301

Dika, S. L., & Singh, K. (2002). Applications of social capital in educational literature: A critical synthesis. Review of Educational Research, 72(1), 31–60.

Duncan, G. J., & Murnane, R. J. (2011). Whither opportunity?: Rising inequality, schools, and children’s life chances. Russell Sage Foundation.

Eccles, J. S., & Barber, B. L. (1999). Student council, volunteering, basketball, or marching band: What kind of extracurricular involvement matters? Journal of Adolescent Research, 14(1), 10–43.

Engle, J., & Tinto, V. (2008). College Success for Low-Income, First-Generation Students. The Pell Institute.

Erikson, E. H. (1968). Identity: Youth and crisis. WW Norton & company.

Fenske, R., Porter, J., & DuBrock, C. (2000). Tracking Financial Aid and Persistence of Women, Minority, and Needy Students in Science, Engineering, and Mathematics. 29.

Fiegener, M. K. (2015). Science and Engineering Degrees, by Race/Ethnicity of Recipients: 2000–12. 163.

Flores, Alfinio. (2007). Examining Disparities in Mathematics Education: Achievement Gap or Opportunity Gap? The High School Journal, 91(1), 29–42. https://doi.org/10.1353/hsj.2007.0022

Flores, L. Y., Navarro, R. L., & Ali, S. R. (2017). The State of SCCT Research in Relation to Social Class: Future Directions. Journal of Career Assessment, 25(1), 6–23. https://doi.org/10.1177/1069072716658649

Fouad, N. A., & Brown, M. T. (2000). Role of race and social class in development: Implications for counseling psychology.

Fouad, N. A., & Santana, M. C. (2017). SCCT and Underrepresented Populations in STEM Fields: Moving the Needle. Journal of Career Assessment, 25(1), 24–39. https://doi.org/10.1177/1069072716658324

Garriott, P. O., Flores, L. Y., & Martens, M. P. (2013). Predicting the math/science career goals of low-income prospective first-generation college students. Journal of Counseling Psychology, 60(2), 200–209. https://doi.org/10.1037/a0032074

Graham, S. E., & Provost, L. E. (2012). Mathematics achievement gaps between suburban students and their rural and urban peers increase over time.

Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2010). Multivariate data analysis: A global perspective (Vol. 7). Upper Saddle River, NJ: Pearson.

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2016). Closing achievement gaps with a utility-value intervention: Disentangling race and social class. Journal of Personality and Social Psychology, 111(5), 745–765. https://doi.org/10.1037/pspp0000075

Hossler, D., Schmit, J., & Vesper, N. (1999). Going to college: How social, economic, and educational factors influence the decisions students make. JHU Press.

Hurtado, S., Newman, C. B., Tran, M. C., & Chang, M. J. (2010). Improving the rate of success for underrepresented racial minorities in STEM fields: Insights from a national project. New Directions for Institutional Research, 2010(148), 5–15.

Huyser, K. R., Sakamoto, A., & Takei, I. (2010). The Persistence of Racial Disadvantage: The Socioeconomic Attainments of Single-Race and Multi-Race Native Americans.

Population Research and Policy Review, 29(4), 541–568. https://doi.org/10.1007/s11113-009-9159-0

Jones, N., & Ramirez, R. (2010). The American Indian and Alaska Native Population: 2010 (p. 21).

Kelly, P. J. (2005). As America becomes more diverse: The impact of state higher education inequality.

Kline, R. B. (2015). Principles and practice of structural equation modeling. Guilford publications.

Kraus, M. W., & Stephens, N. M. (2012). A Road Map for an Emerging Psychology of Social Class: Psychology of Social Class. Social and Personality Psychology Compass, 6(9), 642–656. https://doi.org/10.1111/j.1751-9004.2012.00453.x

Lent, R. W., Brown, S. D., Brenner, B., Chopra, S. B., Davis, T., Talleyrand, R., & Suthakaran, V. (2001). The role of contextual supports and barriers in the choice of math/science educational options: A test of social cognitive hypotheses. Journal of Counseling Psychology, 48(4), 474–483. https://doi.org/10.1037//0022-0167.48.4.474

Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. Journal of Vocational Behavior, 45(1), 79–122.

Lent, R. W., Brown, S. D., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. Journal of Counseling Psychology, 47(1), 36–49. https://doi.org/10.1037//0022-0167.47.1.36

Lent, R. W., Brown, S. D., & Larkin, K. C. (1984). Relation of self-efficacy expectations to academic achievement and persistence. Journal of Counseling Psychology, 31(3), 356.

Lent, R. W., Brown, S. D., Schmidt, J., Brenner, B., Lyons, H., & Treistman, D. (2003). Relation of contextual supports and barriers to choice behavior in engineering majors: Test of alternative social cognitive models. Journal of Counseling Psychology, 50(4), 458–465. https://doi.org/10.1037/0022-0167.50.4.458

Lent, R. W., Brown, S. D., Sheu, H.-B., Schmidt, J., Brenner, B. R., Gloster, C. S., Wilkins, G., Schmidt, L. C., Lyons, H., & Treistman, D. (2005). Social Cognitive Predictors of Academic Interests and Goals in Engineering: Utility for Women and Students at Historically Black Universities. Journal of Counseling Psychology, 52(1), 84–92. https://doi.org/10.1037/0022-0167.52.1.84

Lent, R. W., Sheu, H.-B., Miller, M. J., Cusick, M. E., Penn, L. T., & Truong, N. N. (2018). Predictors of science, technology, engineering, and mathematics choice options: A meta-analytic path analysis of the social–cognitive choice model by gender and race/ethnicity. Journal of Counseling Psychology, 65(1), 17–35. https://doi.org/10.1037/cou0000243

Leppel, K., Williams, M. L., & Waldauer, C. (2001). The impact of parental occupation and socioeconomic status on choice of college major. Journal of Family and Economic Issues, 22(4), 373–394.

Leslie, L. L., McClure, G. T., & Oaxaca, R. L. (1998). Women and minorities in science and engineering: A life sequence analysis. The Journal of Higher Education, 69(3), 239–276.

Li, Y., Alfeld, C., Kennedy, R. P., & Putallaz, M. (2009). Effects of Summer Academic Programs in Middle School on High School Test Scores, Course-Taking, and College Major. Journal of Advanced Academics, 20(3), 404–436. https://doi.org/10.1177/1932202X0902000303

Little, R. J. (1988). A test of missing completely at random for multivariate data with missing values. Journal of the American Statistical Association, 83(404), 1198–1202.

Ma, Y. (2009). Family Socioeconomic Status, Parental Involvement, and College Major Choices—Gender, Race/Ethnic, and Nativity Patterns. Sociological Perspectives, 52(2), 211–234. https://doi.org/10.1525/sop.2009.52.2.211

Maltese, A. V., & Tai, R. H. (2011). Pipeline persistence: Examining the association of educational experiences with earned degrees in STEM among U.S. students. Science Education, 95(5), 877–907. https://doi.org/10.1002/sce.20441

Martinez, J. A., Sher, K. J., Krull, J. L., & Wood, P. K. (2009). Blue-Collar Scholars?: Mediators and Moderators of University Attrition in First-Generation College Students. Journal of College Student Development, 50(1), 87–103. https://doi.org/10.1353/csd.0.0053

McDonough, P. M. (1997). Choosing colleges: How social class and schools structure opportunity. Suny Press.

Miller, L. S. (2004). Promoting Sustained Growth in the Representation of African Americans, Latinos, and Native Americans among Top Students in the United States at All Levels of the Education System. National Research Center on the Gifted and Talented NRCGT.

Moakler, M. W., & Kim, M. M. (2014). College Major Choice in STEM: Revisiting Confidence and Demographic Factors. The Career Development Quarterly, 62(2), 128–142. https://doi.org/10.1002/j.2161-0045.2014.00075.x

Mortenson, T. (2006). National school lunch program participation by state FFY 1993 to FFY 2005. Postsecondary Education Opportunity, 165.

Muijs, D., Harris, A., Chapman, C., Stoll, L., & Russ, J. (2004). Improving schools in socioeconomically disadvantaged areas–A review of research evidence. School Effectiveness and School Improvement, 15(2), 149–175.

Muthén, L. K., & Muthén, B. (2009). Regression analysis, exploratory factor analysis, confirmatory factor analysis, and structural equation modeling for categorical, censored, and count outcomes. Los Angeles: Mplus Short Courses (Topic 2).

Muthén, L., & Muthén, B. (2018). Mplus. The Comprehensive Modelling Program for Applied Researchers: User's Guide, 5.

Nasir, N., Shah, N., Gutierrez, J., Seashore, K., Louie, N., & Baldinger, E. (2011). Mathematics learning and diverse students. National Research Council's Workshop on Successful STEM Education in K–12 Schools, 10–11.

National Science Board. (2010). Preparing the next generation of STEM innovators: Identifying and developing our nation's human capital.

National Science Board. (2018). Science & Engineering Indicators 2018. National Science Board.

National Science Foundation. (2013). Women, minorities and persons with disabilities in science and engineering. National Science Foundation.

Navarro, R. L., Flores, L. Y., & Worthington, R. L. (2007). Mexican American middle school students' goal intentions in mathematics and science: A test of social cognitive career theory. Journal of Counseling Psychology, 54(3), 320–335. https://doi.org/10.1037/0022-0167.54.3.320

Nelson, A. (2002). Unequal treatment: Confronting racial and ethnic disparities in health care. Journal of the National Medical Association, 94(8), 666.

Niu, L. (2017). Family Socioeconomic Status and Choice of STEM Major in College: An Analysis of a National Sample. College Student Journal, 51, 298–312.

Office of Science and Technology Policy. (2016). Reducing the Impact of Bias in the STEM Workforce: Strengthening Excellence and Innovation. Office of Science and Technology Policy.

Oishi, S., Lun, J., & Sherman, G. D. (2007). Residential mobility, self-concept, and positive affect in social interactions. Journal of Personality and Social Psychology, 93(1), 131–141. https://doi.org/10.1037/0022-3514.93.1.131

Orr, M. K., University, P., Ramirez, N. M., University, P., Ohland, M. W., University, P., & Lafayette, W. (2011). Socioeconomic Trends in Engineering: Enrollment, Persistence, and Academic Achievement. 9.

Pascarella, E. T., Pierson, C. T., Wolniak, G. C., & Terenzini, P. T. (2004). First-Generation College Students: Additional Evidence on College Experiences and Outcomes. The Journal of Higher Education, 75(3), 249–284. https://doi.org/10.1353/jhe.2004.0016

Pratt, R. H. (1892). The advantages of mingling Indians with Whites.

R Core Team. (2013). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. http://www.R-project.org/

Rios-Aguilar, C., & Stolzenberg, E. B. (2015). Findings from the 2015 Administration of the Your First College Year (YFCY) Survey. Higher Education Research Institute, UCLA. https://www.heri.ucla.edu/briefs/YFCY/YFCY-2015-Brief.pdf

Rittmayer, A. D., & Beier, M. E. (2008). Overview: Self-efficacy in STEM. SWE-AWE CASEE Overviews, 1, 12.

Ruiz, S., Sharkness, J., Kelly, K., DeAngelo, L., & Pryor, J. H. (2010). Findings from the 2009 Administration of the Your First College Year (YFCY): National Aggregates. Higher Education Research Institute, UCLA. https://www.heri.ucla.edu/PDFs/pubs/Reports/YFCY2009Final_January.pdf https://www.heri.ucla.edu/PDFs/pubs/briefs/HERI_ResearchBrief_OL_2009_YFCY_02_04.pdf

Rumberger, R. W., & Palardy, G. J. (2005). Does Segregation Still Matter? The Impact of Student Composition on Academic Achievement in High School. 47.

Saenz, V., Hurtado, S., Barrera, D., Wolf, D., & Yeung, F. (2007). First in my family: A profile of firstgeneration college students at four-year institutions since 1971: The Foundation for Independent Education.

Satcher, D., & Pamies, R. (2005). Multicultural medicine and health disparities. McGraw-Hill.

Sheu, H.-B., Lent, R. W., Miller, M. J., Penn, L. T., Cusick, M. E., & Truong, N. N. (2018). Sources of self-efficacy and outcome expectations in science, technology, engineering, and mathematics domains: A meta-analysis. Journal of Vocational Behavior, 109, 118–136.

Smith, J. L., Cech, E., Metz, A., Huntoon, M., & Moyer, C. (2014). Giving back or giving up: Native American student experiences in science and engineering. Cultural Diversity and Ethnic Minority Psychology, 20(3), 413–429. https://doi.org/10.1037/a0036945

Solberg, V. S., Hale, J. B., Villarreal, P., & Kavanagh, J. (1993). Development of the College Stress Inventory for Use with Hispanic Populations: A Confinnatory Analytic Approach. Hispanic Journal of Behavioral Sciences, 15(4), 490–497.

Soo Oh, S., & Lewis, G. B. (2011). Stemming inequality? Employment and pay of female and minority scientists and engineers. The Social Science Journal, 48(2), 397–403. https://doi.org/10.1016/j.soscij.2010.11.008

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. Multivariate Behavioral Research, 25(2), 173–180.

Stinebrickner, R., & Stinebrickner, T. R. (2003). Understanding Educational Outcomes of Students from Low-Income Families. 27.

Terenzini, P. T., Springer, L., Yaeger, P. M., Pascarella, E. T., & Nora, A. (1996). First-generation college students: Characteristics, experiences, and cognitive development. Research in Higher Education, 37(1), 1–22. https://doi.org/10.1007/BF01680039

Tierney, W. G., Sallee, M. W., & Venegas, K. M. (2007). Access and Financial Aid: How American-Indian Students Pay for College. Journal of College Admission, 197, 14–23.

Tippeconnic III, J. W., & Tippeconnic Fox, M. J. (2012). American Indian tribal values: A critical consideration in the education of American Indians/Alaska Natives today. International Journal of Qualitative Studies in Education, 25(7), 841–853. https://doi.org/10.1080/09518398.2012.720730

Toutkoushian, R. K., Stollberg, R. A., & Slaton, K. A. (2018). Talking ’Bout My Generation: Defining “First-Generation College Students” in Higher Education Research. Teachers College Record, 38.

Turner, S. L., Joeng, J. R., Sims, M. D., Dade, S. N., & Reid, M. F. (2017). SES, Gender, and STEM Career Interests, Goals, and Actions: A Test of SCCT. Journal of Career Assessment, 106907271774866. https://doi.org/10.1177/1069072717748665

U.S. Bureau of Labor Statistics. (2014). STEM 101: Intro to tomorrow's job. https://www.bls.gov/careeroutlook/2014/spring/art01.pdf

Useem, E. L. (1992). Middle schools and math groups: Parents' involvement in children's placement. Sociology of Education, 263–279.

Usher, E. L., & Pajares, F. (2009). Sources of self-efficacy in mathematics: A validation study. Contemporary Educational Psychology, 34(1), 89–101.

Wang, M., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy–value perspective to understand individual and gender differences in STEM fields. Developmental Review, 33(4), 304–340.

Wang, X. (2013). Why Students Choose STEM Majors: Motivation, High School Learning, and Postsecondary Context of Support. American Educational Research Journal, 50(5), 1081–1121. https://doi.org/10.3102/0002831213488622

Western Interstate Commission for Higher Education (WICHE). (2003). Knocking at the College Door: Projections of High School Graduates By State, Income, and Race/Ethinicity.

Weston, R., & Gore Jr, P. A. (2006). A brief guide to structural equation modeling. The Counseling Psychologist, 34(5), 719–751.

Wiederkehr, V., Darnon, C., Chazal, S., Guimond, S., & Martinot, D. (2015). From social class to self-efficacy: Internalization of low social status pupils' school performance. Social Psychology of Education, 18(4), 769–784. https://doi.org/10.1007/s11218-015-9308-8

Writer, J. H. (2001). Identifying the Identified: The Need for Critical Exploration of Native American Identity within Educational Contexts. Action in Teacher Education, 22(4), 40–47. https://doi.org/10.1080/01626620.2001.10463028

Wuensch, K. L. (2016). An introduction to path analysis. Retrieved From.

Xu, Y. J. (2013). Career Outcomes of STEM and Non-STEM College Graduates: Persistence in Majored-Field and Influential Factors in Career Choices. Research in Higher Education, 54(3), 349–382. https://doi.org/10.1007/s11162-012-9275-2

Yu, C.-Y. (2002). Evaluating cutoff criteria of model fit indices for latent variable models with binary and continuous outcomes (Vol. 30). University of California, Los Angeles Los Angeles, CA

Table 1

Means, standard deviation, minimum and maximum values, and the percentage of missing data

Measure	Mean	SD	Min	Max	Percentage of Missing Data
Family SES	5.18	5.17	1.00	9.00	.00%
School SES	.40	.05	0.00	1.00	.00%
ACT Math	25.20	19.65	0.00	36.00	15.53%
AP Math	2.11	6.42	0.00	10.00	.74%
AP Science	1.27	1.87	0.00	10.00	1.11%
Math Self-Efficacy	3.99	1.63	1.00	6.00	.00%
Identity as a Scientist	2.55	1.30	1.00	5.00	.00%
Financial Stress	2.25	.93	1.00	4.60	.37%
Job Local	2.91	.85	1.00	5.00	.18%
Communal Orientation	5.75	.62	1.00	7.00	.18%
Hours Worked	1.05	2.38	.00	6.00	.00%

Note. N sizes ranged from 457 – 541.

Table 2

Correlation coefficients

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Ethnicity														
2. Gender	-.10*													
3. Family SES	.15**	-.04												
4. School SES	-.26**	.01	-.31**											
5. FGS	-.11*	.02	-.49**	.19**										
6. ACT Math	.19**	-.20**	.15**	-.18**	-.11*									
7. AP Math	.03	-.05	.09*	.01	-.05	.19**								
8. AP Science	.07	-.08	.05	.01	-.04	.17**	.43**							
9. Math Self-Efficacy	.05	-.15**	.06	.01	-.01	.47**	.15**	.10*						
10. Identity as a Scientist	.00	-.07	-.10*	.02	.02	.15**	.11*	.27**	.18**					
11. Financial Stress	-.10*	.10*	-.40**	.19**	.23**	-.15**	-.09*	-.05	-.16**	.03				
12. Job Locally	-.09*	.06	.07	.03	-.02	-.08	-.07	-.08	.05	.03	.02			
13. Communal	-.09*	.14**	.03	.03	-.03	-.09	-.03	-.01	.01	.04	.05	.24**		
14. Hours Worked	.01	.09*	-.19**	.11*	.10*	-.03	-.02	-.08	-.01	.09*	.28**	.02	.02	
15. STEM-major	.01	-.12**	-.07	.01	.04	.21**	.08	.16**	.22**	.56**	-.07	.08	-.04	.00

Note. ** p < .01, * p < .05

Table 3

Parameter estimates

Variable	*B*	*β*	*CP*
StemCode			
Identity as a Scientist	.57 (.04)**	.63 (.04)**	.20
Math Self-Efficacy	.18 (.04)**	.22 (.05)**	.07
Family SES	-.08 (.03)*	-.17 (.06)*	-.03
School SES	.02 (.24)	.01 (.05)	
First-generation status	.03 (.12)	.02 (.06)	
Concern with Finding a Job Locally	.14 (.06)*	.13 (.06)*	.05
Financial Stress	-.15 (.07)*	-.14 (.06)*	-.06
Hours Worked Per Week	.02 (.04)	.03 (.06)	
Communal Orientation	-.06 (.08)	-.05 (.06)	
Gender	-.15 (.10)	-.07 (.05)	
Ethnicity	.01 (.05)	.01 (.05)	
Identity as a Scientist			
ACT Math	.05 (.02)**	.21 (.06)**	
AP Math Courses Taken	-.03 (.03)	-.07 (.06)	
AP Science Courses Taken	.27 (.05)**	.32 (.06)**	
Gender	-.02 (.11)	-.01 (.05)	
Ethnicity	-.05 (.06)	-.04 (.05)	
Math Self-Efficacy			
ACT Math	.14 (.02)**	.49 (.05)**	
AP Math Courses Taken	.01 (.19)	.01 (.05)	
AP Science Courses Taken	.08 (.10)	.09 (.05)	
Gender	-.13 (.08)	-.05 (.04)	
Ethnicity	-.05 (.05)	-.04 (.04)	

(*continued*)

(*continued*) **Table 3**

Variable	*B*	*β*	*CP*
Financial Stress			
Family SES	-.15 (.02)**	-.35 (.05)**	
School SES	.33 (.19)	.07 (.04)	
First-generation status	.08 (.10)	.04 (.05)	
Gender	.17 (.08)*	.09 (.04)*	
Ethnicity	-.01(.86)	-.01 (.04)	
Communal Orientation			
Family SES	.01 (.02)	.04 (.05)	
School SES	.11 (.15)	.03 (.04)	
First-generation status	-.04 (.08)	-.03 (.05)	
Gender	.23 (.07)**	.14 (.04)**	
Ethnicity	-.07 (.09)	-.08 (.05)	
Concern with Finding a Job Locally			
Family SES	.04 (.02)	.11 (.05)	
School SES	.13 (.20)	.03 (.05)	
First-generation status	.03 (.10)	.02 (.05)	
Gender	.10 (.08)	.05 (.04)	
Ethnicity	-.09 (.04)*	-.09 (.04)*	
Number of Hours Worked per Week			
Family SES	-.12 (.04)**	-.17 (.05)**	
School SES	.50 (.33)	.07 (.05)	
First-generation status	.00 (.17)	.00 (.05)	
Gender	.27 (.14)	.08 (.04)	
Ethnicity	.10 (.07)	.06 (.05)	

(*continued*)

(*continued*) **Table 3**

Variable	*B*	*β*	*CP*
Act Math			
Family SES	-.154 (.11)	-.19 (.05)	
School SES	-1.62 (.99)	.13 (.05)	
First-generation status	-.18 (.48)	.07 (.05)	
Gender	-1.72 (.42)**	-.08 (.05)**	
Ethnicity	.62 (.22)**	-.02 (.05)**	
Number of AP Math Courses Taken			
Family SES	.11 (.06)*	-.04 (.05)*	
School SES	.57 (.56)	.02 (.05)	
First-generation status	-.04 (.26)	.10 (.05)	
Gender	.23 (.22)	.05 (.04)	
Ethnicity	-.07 (.12)	-.01 (.04)	
Number of AP Science Courses Taken			
Family SES	.04 (.03)	-.08 (.05)	
School SES	.13 (.30)	.07 (.05)	
First-generation status	.03 (.15)	.00 (.05)	
Gender	.10 (.13)	.05 (.05)	
Ethnicity	-.09 (.06)	-.02 (.04)	

Note. Standard errors for raw and standardized estimates are presented in parenthesis. CP = calculated probability for significant effects.
* p < .05, ** p < .01.

Table 4

Summary of Indirect Effects.

Path/Effect	*B*	*β*	*95% CI*
StemCode			
<- Financial Stress <- Family SES	.02 (.00)*	.05 (.02)*	(.01, .09)
<- Finding a Job Locally <- Family SES	.00 (.00)	.01 (.00)	(.00, .01)
<- Hours Worked Per Week <- Family SES	.00 (.00)	.00 (.00)	(-.02, .01)
<- Communal Orientation <- Family SES	-.00 (.00)	-.00 (.00)	(-.00, .00)
<- Financial Stress <- School SES	-.05 (.03)	-.01 (.00)	(-.03, -.00)
<- Finding a Job Locally <- School SES	.01 (.03)	.00 (.01)	(-.00, .02)
<- Hours Worked Per Week <- School SES	.00 (.01)	.00 (.00)	(-.00, .00)
<- Communal Orientation <- School SES	-.00 (.00)	-.00 (.00)	(-.01, .00)
<- Financial Stress <- First-generation status	-.01 (.01)	-.01 (.00)	(-.02, .00)
<- Finding a Job Locally <- First-generation status	.00 (.01)	.00 (.01)	(-.00, .01)
<- Hours Worked Per Week <- First-generation status	.00 (.00)	.00 (.00)	(-.01, .00)
<- Communal Orientation <- First- generation status	.00 (.00)	.00 (.00)	(-.00, .01)

Note. Standard errors for raw and standardized estimates are presented in parenthesis. CI = confidence interval for standardized results.
* $p < .05$, ** $p < .01$.

Table 5

Model Fit Indices for hypothesized and alternative models

Model	χ^2	*df*	RMSEA	90% CI RMSEA	WRMR	CFI	TLI
Hypothesized Model	225.57*	39	.09	(.08, .11)	1.45	.70	.27
Modified Hypothesized Model	88.13*	36	.05	(.04, .06)	.88	.92	.78
Trimmed Hypothesized Model	97.22*	47	.04	(.03, .06)	.97	.92	.86
Alternative Model	259.56	53	.09	(.08, .10)	1.54	.67	.41
Final Alternative Model	120.92	50	.05	(.04, .06)	1.03	.89	.79

Note. *$p < 0.01$

Figure 1

Social Cognitive Career Theory model

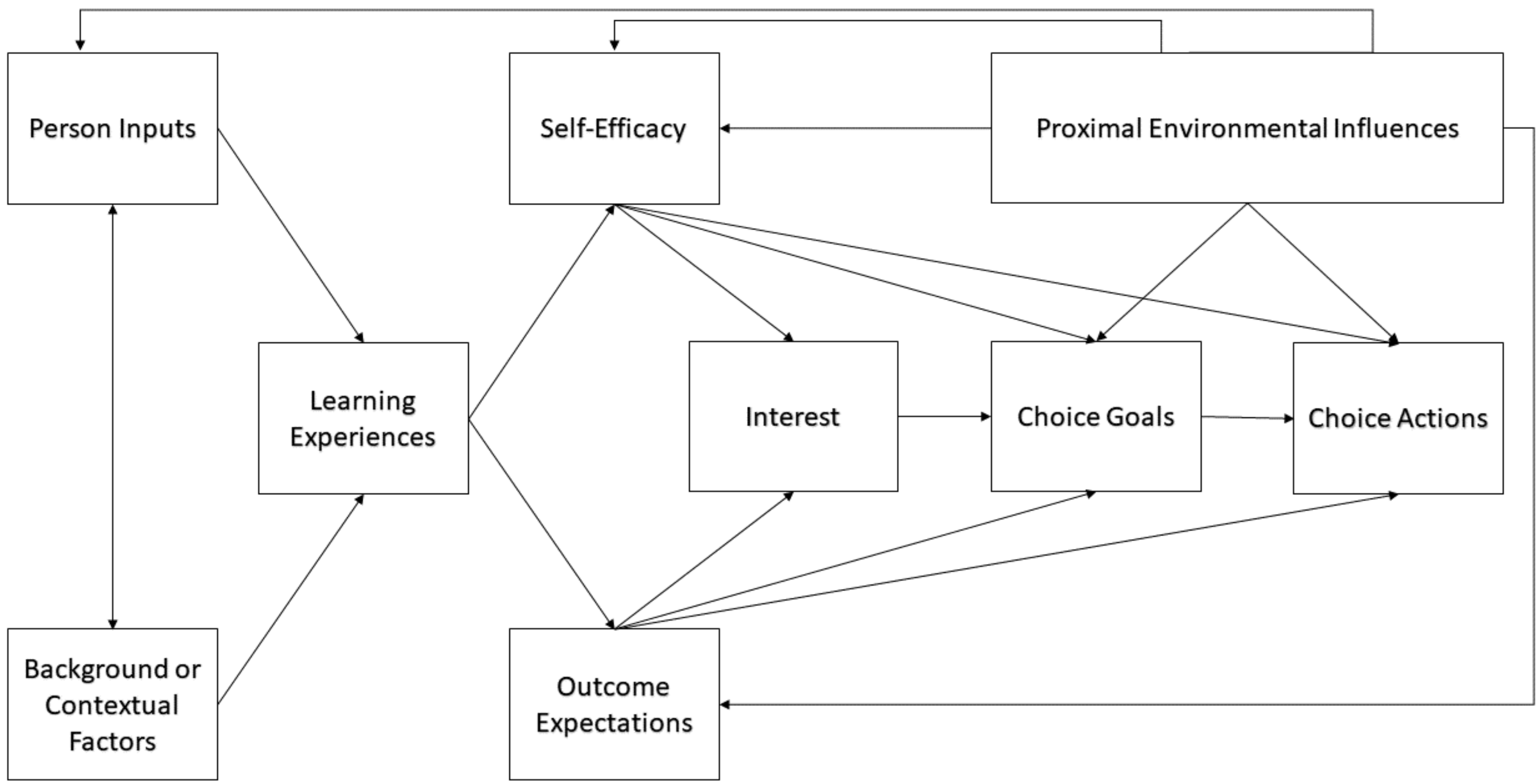


Figure 2

A revised version of SCCT's person input, background/contextual affordances, and self-efficacy model

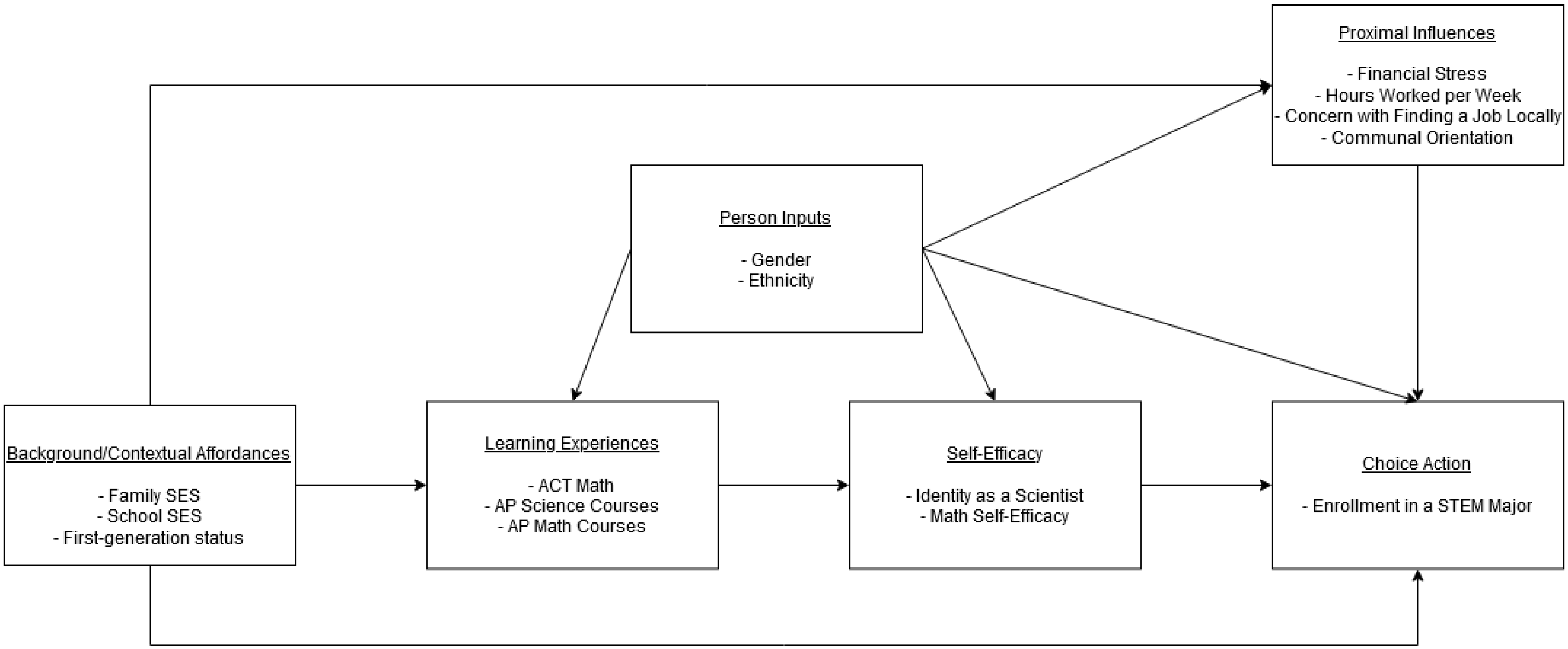
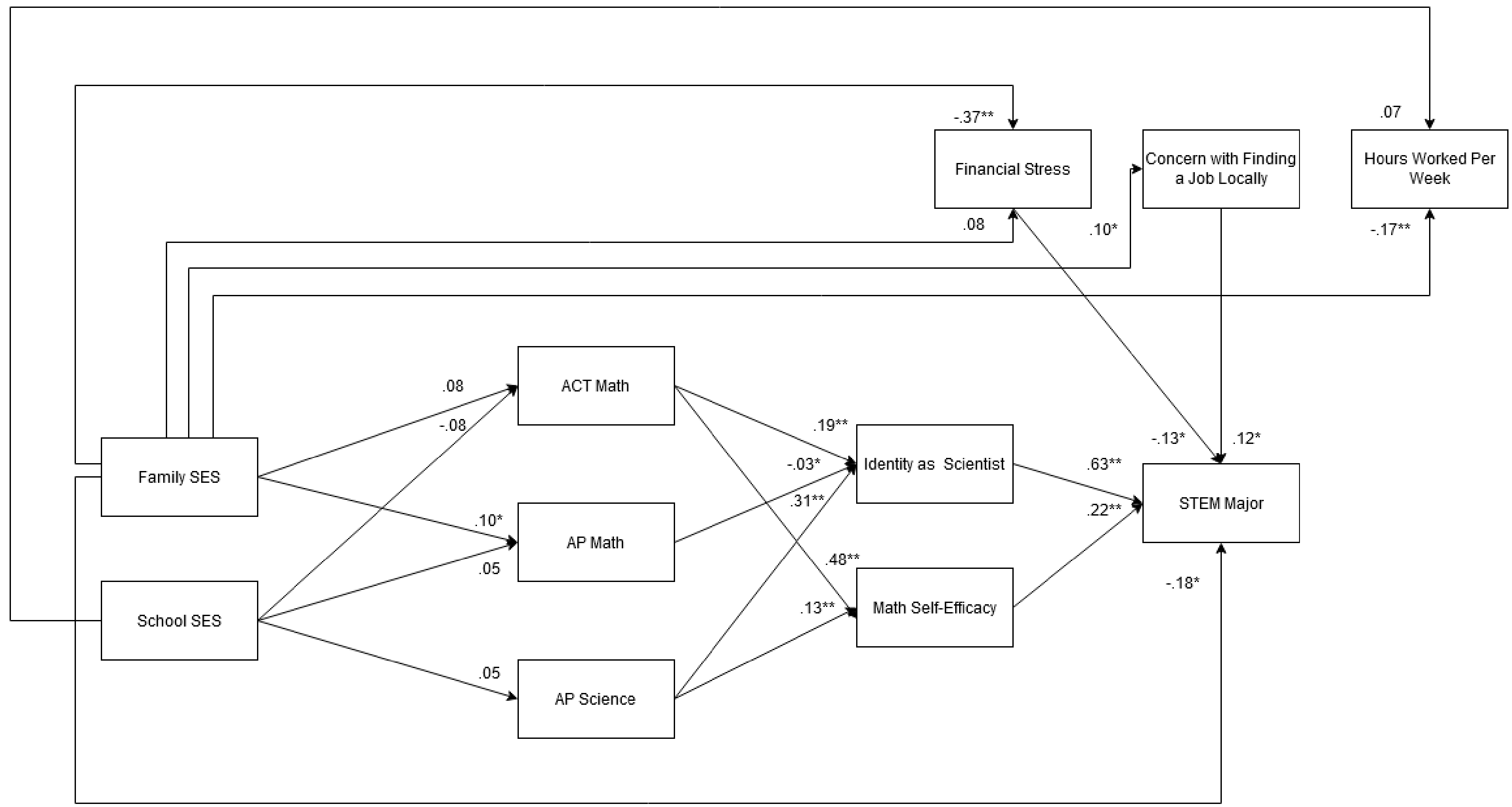


Figure 3

Trimmed model and corresponding standardized parameter estimates



Note. Gender and Ethnicity are not included in the figure for ease for interpretation.